In [249]:
```
import numpy as np
import pandas as pd
import random
import timeit
import seaborn as sns
sns.set(style="ticks", color_codes=True)
from sklearn import neighbors
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
```

In [2]:
```
#Columns/Features
D = ['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH'
, 'sulphates', 'alcohol']
L = 'quality'
C = 'color'
DL = D + [L]
DC = D + [C]
DLC = DL + [C]

#Loading Data set
wine_r = pd.read_csv("winequality-red.csv", sep=';')
#Loading Data set
wine_w = pd.read_csv("winequality-white.csv", sep=';')
wine_w= wine_w.copy()
#a new object with copy of objects data nd indices.
wine_w[C]= np.zeros(wine_w.shape[0])
#returns a new array of given shape and size filled with zeros
wine_r[C]= np.ones(wine_r.shape[0])
wine = pd.concat([wine_w,wine_r])
```

In [3]:
```
wine_w
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.0	0.27	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8
1	6.3	0.30	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9
2	8.1	0.28	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10
3	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9
4	7.2	0.23	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9
...	...	...	...	...	...	...	...	...	...	...	
4893	6.2	0.21	0.29	1.6	0.039	24.0	92.0	0.99114	3.27	0.50	11
4894	6.6	0.32	0.36	8.0	0.047	57.0	168.0	0.99490	3.15	0.46	9
4895	6.5	0.24	0.19	1.2	0.041	30.0	111.0	0.99254	2.99	0.46	9
4896	5.5	0.29	0.30	1.1	0.022	20.0	110.0	0.98869	3.34	0.38	12
4897	6.0	0.21	0.38	0.8	0.020	22.0	98.0	0.98941	3.26	0.32	11

4898 rows × 13 columns

In [4]:
```
wine_r
```

Out[4]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9
1	7.8	0.880	0.00	2.6	0.098	25.0	67.0	0.99680	3.20	0.68	9
2	7.8	0.760	0.04	2.3	0.092	15.0	54.0	0.99700	3.26	0.65	9
3	11.2	0.280	0.56	1.9	0.075	17.0	60.0	0.99800	3.16	0.58	9
4	7.4	0.700	0.00	1.9	0.076	11.0	34.0	0.99780	3.51	0.56	9
...	...	...	...	...	...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11

1599 rows × 13 columns

In [5]:
```
#none normalized
```

In [6]:
```
wine
```

Out[6]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.0	0.270	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8
1	6.3	0.300	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9
2	8.1	0.280	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10
3	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9
4	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9
...	...	...	...	...	...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11

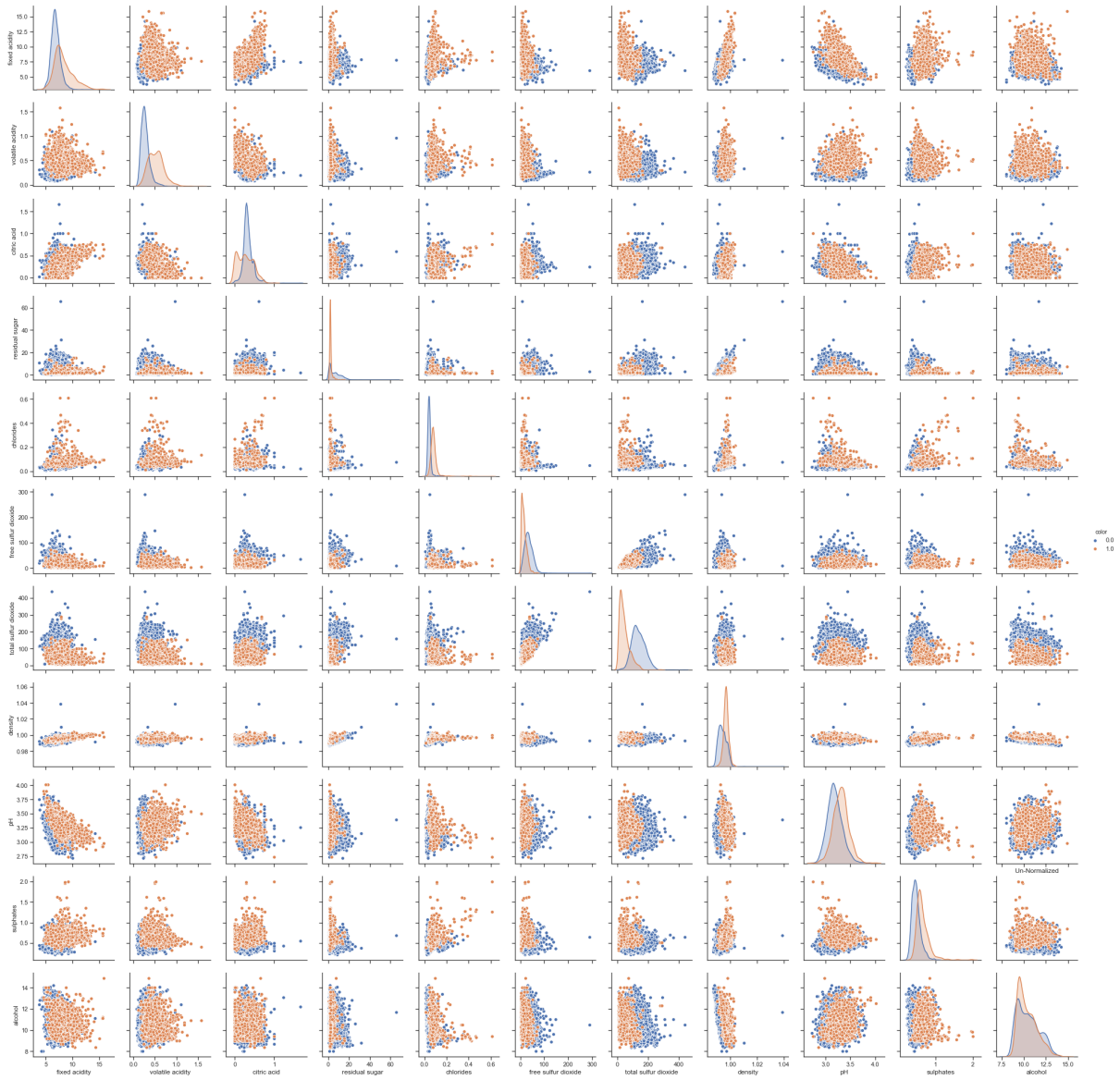
6497 rows × 13 columns

PART-1 : PAIR PLOTS

Unnormalized pair plot

In [7]:
```
sns.pairplot(wine,vars=wine[D],hue="color")
sns.set_style('whitegrid')
plt.title("Un-Normalized")
```

Out[7]: Text(0.5, 1, 'Un-Normalized')



In [8]:
```
# print(wine.shape)
# wine[D].describe()
# wine[D].head()
```

In [9]:
```
# print(wine.shape)
# wine[DLC].describe()
# wine[DLC].head()
```

zscore normalized fully normalizing the data for pair plot

In [10]:
```
#can also be done by :::::
#wine_normalized=StandardScaler().fit_transform(wine[D])
# returns numpy array
#canm also be done by scipy
wine_normalized_for_pairplot=((wine-wine.mean())/wine.std())#normalizing whole dataset. This can also be done using StandardScaler().
wine_normalized_for_pairplot['color']=wine['color'] #replacing color and quality
wine_normalized_for_pairplot['quality']=wine['quality']
```

In [11]:
```
wine_normalized_for_pairplot.std()
```

Out[11]:
```
fixed acidity           1.000000
volatile acidity        1.000000
citric acid             1.000000
residual sugar          1.000000
chlorides               1.000000
free sulfur dioxide     1.000000
total sulfur dioxide    1.000000
density                 1.000000
pH                      1.000000
sulphates               1.000000
alcohol                 1.000000
quality                 0.873255
color                   0.430779
dtype: float64
```

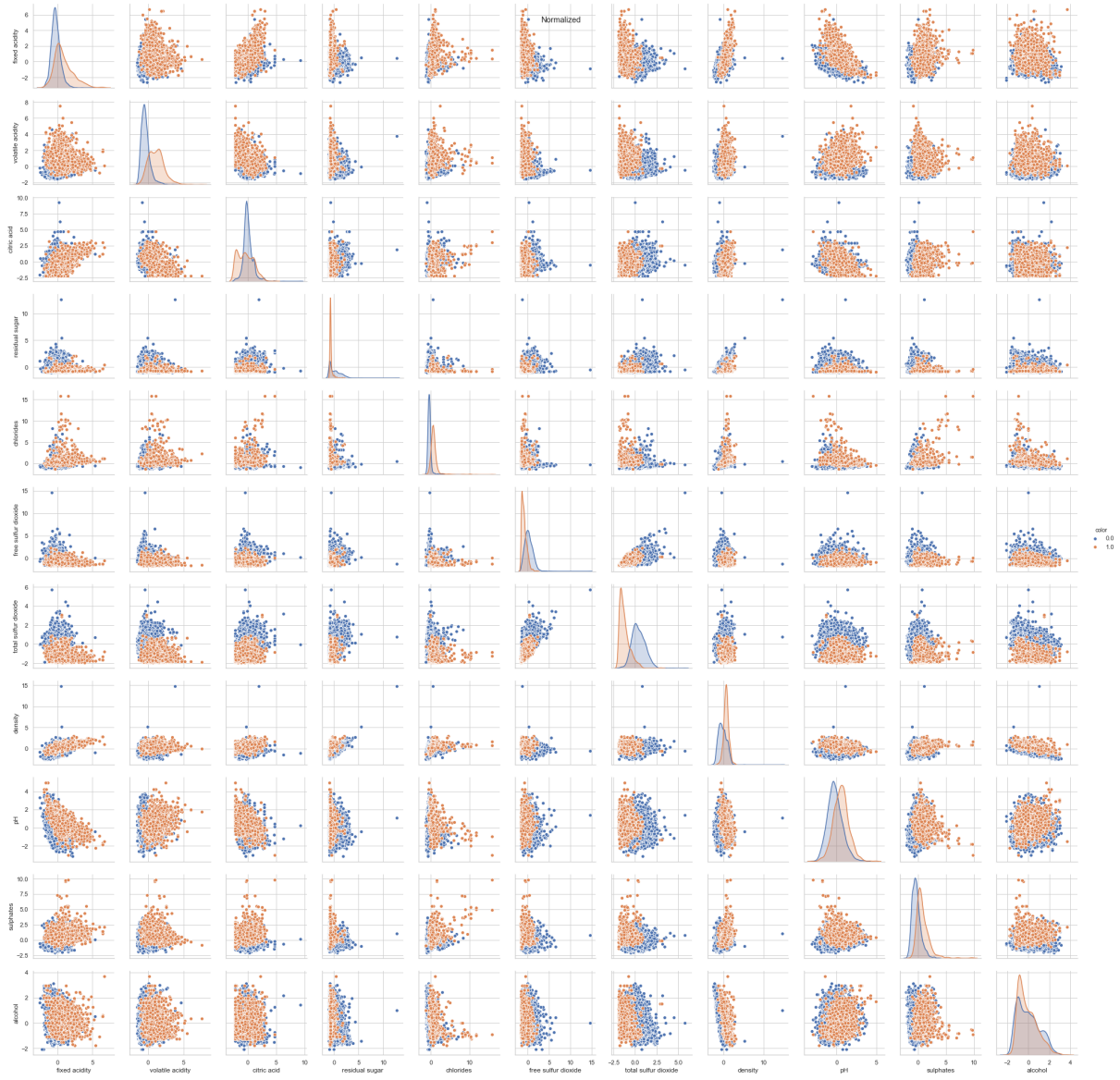
In [12]:
```
wine_normalized_for_pairplot.mean()
```

Out[12]:
```
fixed acidity           9.426335e-15
volatile acidity       -2.682491e-15
citric acid             2.983593e-14
residual sugar         -3.354977e-15
chlorides              -6.889107e-15
free sulfur dioxide    -1.210787e-15
total sulfur dioxide    4.524966e-17
density                 1.736770e-12
pH                      2.660711e-14
sulphates              -8.569890e-15
alcohol                -4.778225e-14
quality                 5.818378e+00
color                   2.461136e-01
dtype: float64
```

Normalized pair plot

In [13]:
```
plotting_2=sns.pairplot(wine_normalized_for_pairplot,vars=wine_normalized_for_pairplot[D],hue='color')
sns.set_style('whitegrid')
plotting_2.fig.suptitle("Normalized")
```

Out[13]: Text(0.5, 0.98, 'Normalized')



ANALYSIS::-

Normalization Technique:: z-score

wine_normalized=((wine-wine.mean())/wine.std())

Need of Normalization::

Data is normalized so that all the features are on the same scale and one feature doesn't end up dominating others due to the variations in the scale when we try to fit the data into a model. The z-scores have a distribution with a mean of 0 and a standard deviation of 1.

Pair Plots::

1) Unnormalized pair plots :

It can be clearly seen that the scales for various features are varying hugely viz.

chlorides: max val: 0.6 i.e small variations in the data should have larger effect on the model during classification.

total sulfur dioxide: max val: 400 i.e small variations in the data should have little effect on the model during classification.

2) Normalized pair plots :

Z score normalization has scaled the data points to a common scale ranging between -2 and 15 with 0 mean and s.d as 1.

chlorides: max val: 15

total sulfur dioxide: max val: 6

Now, all the features in the dataset will have the equalized dominance with respect to units when classification is done.

Density feature::

Density when plotted with other features in unnormalized pairplot can been seen less separable and having overlapped data points for class 0 and class 1 of label "color". Whereas, the density when plotted with other features after normalization over a scale of 0-15 is separating the datapoints very clearly.

Note:Correlation wise feature-feature analysis is given in feature selection section

Citations:

1.https://statistics.laerd.com/statistical-guides/standard-score-2.php

2.https://stats.stackexchange.com/questions/69157/why-do-we-need-to-normalize-data-before-principal-component-analysis-pca

PART-2 :: KNN --> NORMALIZED AND UNNORMALIZED

SPLITTING THE DATASET INTO TRAIN TEST (80 : 20) AND THEN PERFORMING NORMALIZATION SEPARATELY TAKING MEAN AND STD DEV OF TRAINSET FOR TESTSET AS WELL. LABEL -->COLOR

In [14]:
```
X=wine[D]
y=wine[C]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ra
ndom_state = 42)
```

Normalization

In [15]:
```
#numpy array
wine_normalized_X_train=((X_train-X_train.mean())/X_train.std())
#normalizing train set. This can also be done using StandardScaler() or z s
core or fit_transform and transform for test_data.
wine_normalized_X_test=((X_test-X_train.mean())/X_train.std())
```

In real world, we don't have access to the test data so we apply the normalization on the train data and then use the same mean and standard deviation for the unknown data. Even if we have the test data and try to normalize the whole dataset before splitting, we are passing the information about our test data into the model which may increase the accuracy of the model for that set but when novel data is fed into the model, it will generalize poor on it.

Citations:

1.https://stackoverflow.com/a/49444783

2.https://www.statisticshowto.datasciencecentral.com/normalized/

3.https://stackoverflow.com/questions/42092448/accuracy-difference-on-normalization-in-knn

KNN --> 3 WEIGHTS || WITHOUT FEATURE EX || UN-NORMALIZED DATA

In [16]:
```
start = timeit.default_timer()

n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.
for k in n_neighborslist:
    neigh = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_names
[0],p=2)
    neigh.fit(X_train, y_train)
    y_pred = neigh.predict(X_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh1 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=1)
    neigh1.fit(X_train, y_train)
    y_pred1 = neigh1.predict(X_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh2 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=2)
    neigh2.fit(X_train, y_train)
    y_pred2 = neigh2.predict(X_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2


stop = timeit.default_timer()
print('Time unnormalized KNN: ', stop - start)

Timetaken = pd.DataFrame(columns = ['Model', 'time'])
Timetaken = Timetaken.append({'Model':'Unnormalized KNN', 'time':stop-start
},ignore_index=True)
```

```
Time unnormalized KNN:  11.168142673000006
```

CONFUSION MATRIX -MISCLASSIFICATIONS || K (HIGHEST ACCURACY)

In [17]:
```
neigh = neighbors.KNeighborsClassifier(n_neighbors=1,weights=col_names[0],p
=2)
neigh.fit(X_train, y_train)
y_pred = neigh.predict(X_test)


neigh1 = neighbors.KNeighborsClassifier(n_neighbors=5, weights='distance',p
=1)
neigh1.fit(X_train, y_train)
y_pred1 = neigh1.predict(X_test)


neigh2 = neighbors.KNeighborsClassifier(n_neighbors=6, weights='distance',p
=2)
neigh2.fit(X_train, y_train)
y_pred2 = neigh2.predict(X_test)
```

In [18]:
```
a=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
b=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
c=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
```

In [19]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=1")
a
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=1
```

Out[19]:

Predicted	0.0	1.0	All
True			
0.0	958	28	986
1.0	37	277	314
All	995	305	1300

In [20]:
```
print("CONFUSION MATRIX || DISTANCE MANHATTAN || K=5")
b
```

```
CONFUSION MATRIX || DISTANCE MANHATTAN || K=5
```

Out[20]:

Predicted	0.0	1.0	All
True			
0.0	970	16	986
1.0	34	280	314
All	1004	296	1300

In [21]:
```
print("CONFUSION MATRIX || DISTANCE EUCLIDEAN || K=6")
c
```

```
CONFUSION MATRIX || DISTANCE EUCLIDEAN || K=6
```

Out[21]:

Predicted	0.0	1.0	All
True			
0.0	969	17	986
1.0	46	268	314
All	1015	285	1300

In [22]:
```
Timetaken
```

Out[22]:

	Model	time
0	Unnormalized KNN	11.168143

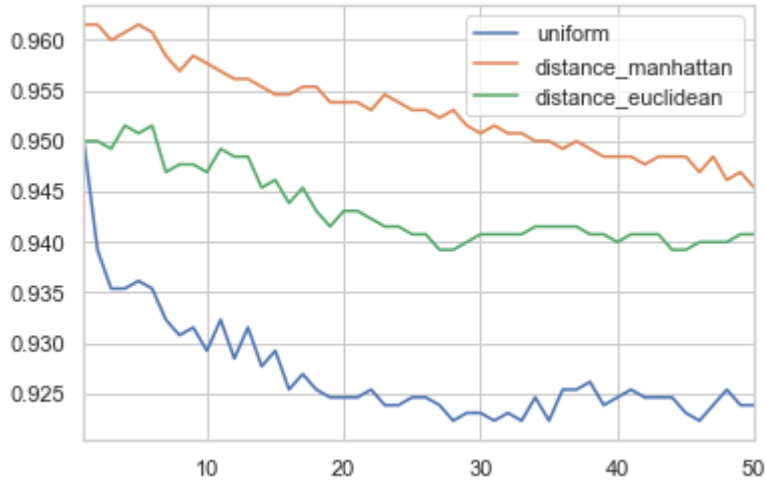
In [23]:
```
acc.describe()
```

Out[23]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.927046	0.953062	0.943369
std	0.005373	0.004460	0.003816
min	0.922308	0.945385	0.939231
25%	0.923846	0.949231	0.940769
50%	0.924615	0.953077	0.941538
75%	0.929038	0.955962	0.946731
max	0.950000	0.961538	0.951538

In [25]:
```
acc[:].plot.line()
```

Out[25]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f36410af88>
```



KNN --> 3 WEIGHTS || WITHOUT FEATURE EX || NORMALIZED DATA

In [26]:
```
start = timeit.default_timer()

n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh4 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_name
s[0],p=2)
    neigh4.fit(wine_normalized_X_train, y_train)
    y_pred = neigh4.predict(wine_normalized_X_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh5 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=1)
    neigh5.fit(wine_normalized_X_train, y_train)
    y_pred1 = neigh5.predict(wine_normalized_X_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh6 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=2)
    neigh6.fit(wine_normalized_X_train, y_train)
    y_pred2 = neigh6.predict(wine_normalized_X_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2

stop = timeit.default_timer()
print('Normalized KNN: ', stop - start)

Timetaken = Timetaken.append({'Model':'Normalized KNN', 'time':stop-start},
ignore_index=True)
```

```
Normalized KNN:  41.344797043
```

CONFUSION MATRIX -MISCLASSIFICATIONS || K (HIGHEST ACCURACY)

In [27]:
```
neigh4 = neighbors.KNeighborsClassifier(n_neighbors=3, weights=col_names[0
],p=2)
neigh4.fit(wine_normalized_X_train, y_train)
y_pred = neigh4.predict(wine_normalized_X_test)


neigh5 = neighbors.KNeighborsClassifier(n_neighbors=21, weights='distance',
p=1)
neigh5.fit(wine_normalized_X_train, y_train)
y_pred1 = neigh5.predict(wine_normalized_X_test)


neigh6 = neighbors.KNeighborsClassifier(n_neighbors=3, weights='distance',p
=2)
neigh6.fit(wine_normalized_X_train, y_train)
y_pred2 = neigh6.predict(wine_normalized_X_test)
```

In [28]:
```
d=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
e=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
f=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
```

In [29]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=3")
d
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=3
```

Out[29]:

Predicted	0.0	1.0	All
True			
0.0	985	1	986
1.0	5	309	314
All	990	310	1300

In [30]:
```
print("CONFUSION MATRIX || DISTANCE MANHATTAN || K=21")
e
```

```
CONFUSION MATRIX || DISTANCE MANHATTAN || K=21
```

Out[30]:

Predicted	0.0	1.0	All
True			
0.0	985	1	986
1.0	3	311	314
All	988	312	1300

In [31]:
```
print("CONFUSION MATRIX || DISTANCE EUCLIDEAN || K=3")
e
```

```
CONFUSION MATRIX || DISTANCE EUCLIDEAN || K=3
```

Out[31]:

Predicted	0.0	1.0	All
True			
0.0	985	1	986
1.0	3	311	314
All	988	312	1300

In [32]:
```
Timetaken
```

Out[32]:

	Model	time
0	Unnormalized KNN	11.168143
1	Normalized KNN	41.344797

In [33]:
```
acc.describe()
```

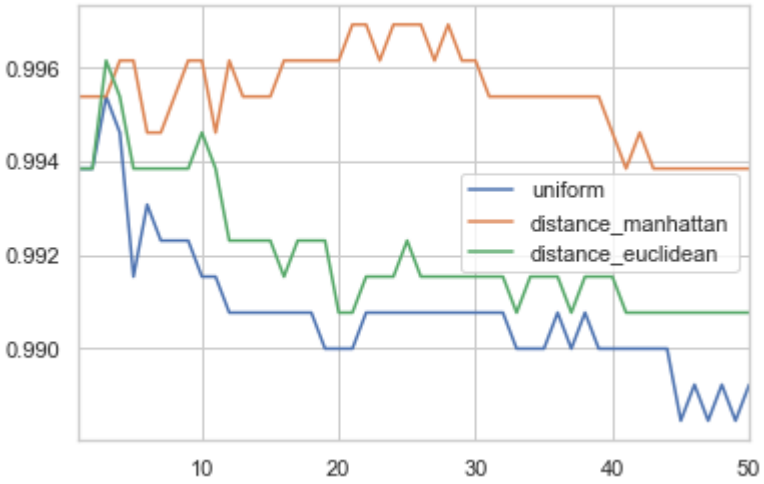
Out[33]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.990815	0.995431	0.992046
std	0.001428	0.000976	0.001342
min	0.988462	0.993846	0.990769
25%	0.990000	0.994615	0.990769
50%	0.990769	0.995385	0.991538
75%	0.990769	0.996154	0.992308
max	0.995385	0.996923	0.996154

In [34]:
```
# acc
```

In [35]:
```
acc[:].plot.line()
#acc.plot(style='.-')
```

Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1f366bf8448>



ANALYSIS::-Normalized and Unnormalized KNN || Weighting schemes-->3 ||Label : color

U.E--> Uniform Euclidean, D.M--> Distance Manhattan, D.E--> Distance Euclidean

Unnormalized KNN::

Performance analysis::

1.Time taken: Time taken: 11 s

2.Misclassification (AT BEST VALUE OF K): For U.E, there are total 65 miclassifications out of which color label 1 is misclassfied 37 times whereas D.M misclassifies color label 1 for 34 times with total 50 misclassifications and D.E leading to 46 misclassifications for color label 1 with a total nearing to 63 which is close to D.M.

3.Mean Accuracy: The mean accuracies for D.M,D.E,U.E are 95.30%,94.33% and 92.70%.

4.Best k values: K=1(overfitting) gives the best accuracy i.e 95% for U.E after which it falls substantially. For D.M k=5 gives highest accuracy of 96.15% with little decrease in accuracy w.r.t increasing k whereas D.E gives 95.15% accuracy at k=6.

Normalized KNN::

Performance analysis::

1.Time taken: Time taken: 35 s

2.Misclassifictaion(AT BEST VALUE OF K) : For U.E, there are total 6 miclassifications out of which color label 0 is misclassfied 1 times whereas D.M misclassifies color label 0 for 1 time with total 4 misclassifications and D.E leading to 1 misclassifications for color label 0 with a total nearing to 4 which is close to U.E.

3.Mean Accuracy: The mean accuracies for D.M,D.E,U.E are 99.54%, 99.20% and 99.08%.

4.Best k values: K=3 gives the best accuracy i.e 99.53% for U.E after which it falls substantially. For D.M k=21,22,24,25,26 gives highest accuracy of 96.69% with little decrease in accuracy w.r.t increasing k whereas D.E gives 99.61% accuracy at k=3.

Results:

1.EXECUTION TIME: Combined time taken by all the 3 weighting schemes in KNN for unnormalized data is very less i.e 11 sec which averages to 3.7 seconds per weighting scheme as compared to the time taken by KNN for normalized data which is approximately 3 times taken for unnormalized data i.e 35 seconds.

2.MISCLASSIFICATION ERROR(AT BEST VALUE OF K): From the confusion matrix,for unnormalized data, it can be clearly seen that all the 3 weighting schemes used in KNN are misclassifying a lot of data points but they are classifying COLOR LABEL=0 very well. Whereas in case of normalized data, the misclassifications by the model fell down drastically and both the color labels i.e 0 and 1 are being classified properly with fewer error classifications.

3.MEAN ACCURACY: It can be clearly seen that there is a substantial change in the mean accuracies of the model when fed with normalized and unnormalized data. It can also be inferred that in both the cases, taking "distance" weights with p=1 i.e manhattan for minkowski metric comes to have the highest mean accuracy so far which is 99.54%(normalized data),95.30%(unnormalized data) and 99.69(norm),96.15(unnorm) as the highest accuracy at k=21,22,24,25,26(norm), k=5(unnorm) which proves that the combination of zscore and distance manhattan is the best scheme explored till now in this case.

4.Best K values: For Normalized data, the best k values for U.E and D.E is found to be 3 whereas for Distance manhattan there are multiple k values (21,22,24,25,26) giving the highest accuracy. For unnormalized data, Distance manhattan gives the highest accuracy at k=5. Thus, Distance mahattan used in KNN for normalized data gives the highest accuracy at multiple k values which are not causing any overfitting and bias.

Citations:

1.https://statistics.laerd.com/statistical-guides/standard-score-2.php

2.https://stats.stackexchange.com/questions/69157/why-do-we-need-to-normalize-data-before-principal-component-analysis-pca

3.https://towardsdatascience.com/importance-of-distance-metrics-in-machine-learning-modelling-e51395ffe60d

In [ ]:

Optional bonus 1 : Better than Znorm and Manhattan

Minmax norm-Not better

Minmax normalization linearly transforms x to y= (x-min)/(max-min), where min and max are the minimum and maximum values in x.

In [159]:
```
wine_normalized_min_max=((wine-wine.min())/(wine.max() - wine.min()))
wine_normalized_min_max['color']=wine['color'] # - color and quality
wine_normalized_min_max['quality']=wine['quality']
```

In [160]:
```
x_min_max=wine_normalized_min_max[D]
y_min_max=wine_normalized_min_max[C]
X_train_min_max, X_test_min_max, y_train_min_max, y_test_min_max = train_te
st_split(x_min_max, y_min_max, test_size=0.2, random_state = 42)
```

In [161]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:


    neigh148 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='dista
nce',metric='chebyshev')
    neigh148.fit(X_train_min_max, y_train)
    y_pred1 = neigh148.predict(X_test_min_max)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1
```

In [162]:
```
acc.describe()
```

Out[162]:

	uniform	distance_manhattan	distance_euclidean
count	50.0	50.000000	50.0
mean	0.0	0.984308	0.0
std	0.0	0.002701	0.0
min	0.0	0.981538	0.0
25%	0.0	0.981731	0.0
50%	0.0	0.983077	0.0
75%	0.0	0.986923	0.0
max	0.0	0.990000	0.0

metric=max(|x - y|) not better giving 94%

Tried other metrics as well. Didn't succeed.

optional bonus 2- feature selection

In [36]:
```
wine
```

Out[36]:

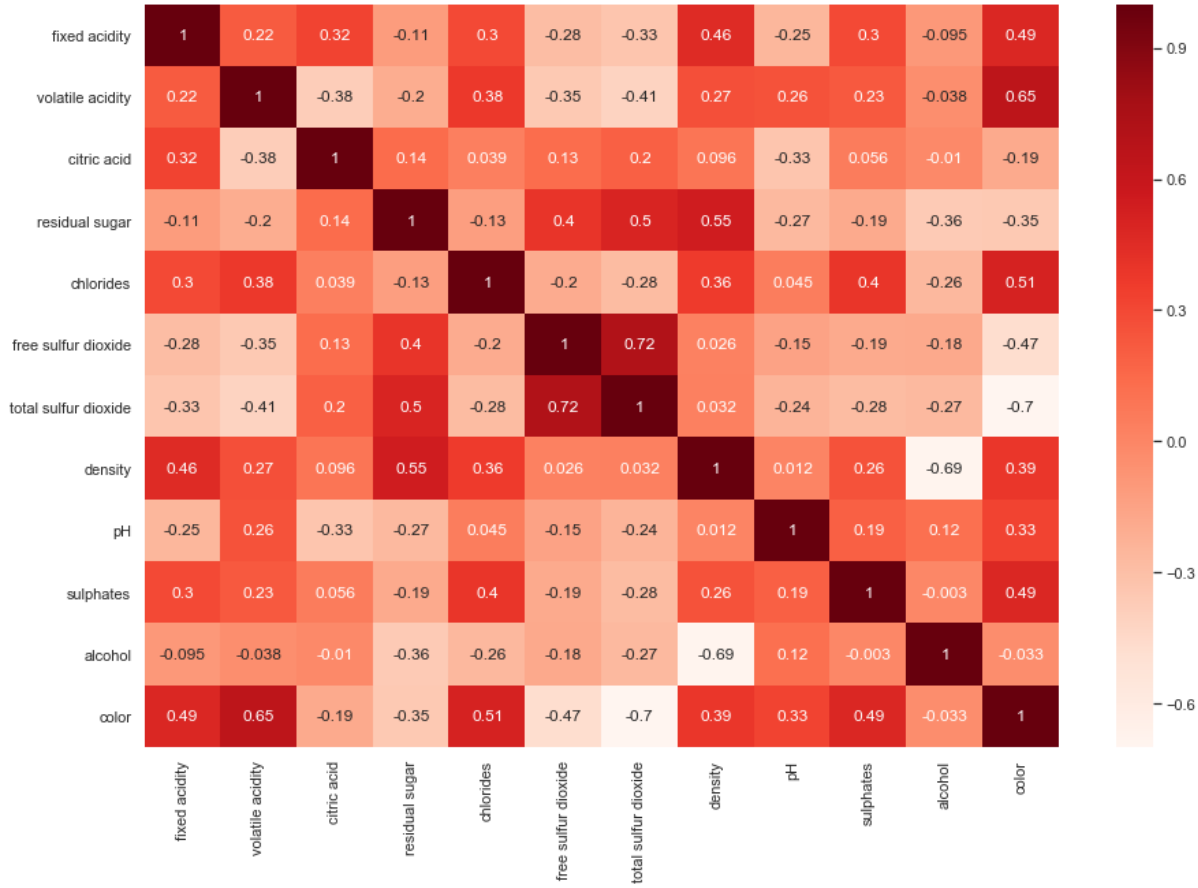
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.0	0.270	0.36	20.7	0.045	45.0	170.0	1.00100	3.00	0.45	8
1	6.3	0.300	0.34	1.6	0.049	14.0	132.0	0.99400	3.30	0.49	9
2	8.1	0.280	0.40	6.9	0.050	30.0	97.0	0.99510	3.26	0.44	10
3	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9
4	7.2	0.230	0.32	8.5	0.058	47.0	186.0	0.99560	3.19	0.40	9
...	...	...	...	...	...	...	...	...	...	...	
1594	6.2	0.600	0.08	2.0	0.090	32.0	44.0	0.99490	3.45	0.58	10
1595	5.9	0.550	0.10	2.2	0.062	39.0	51.0	0.99512	3.52	0.76	11
1596	6.3	0.510	0.13	2.3	0.076	29.0	40.0	0.99574	3.42	0.75	11
1597	5.9	0.645	0.12	2.0	0.075	32.0	44.0	0.99547	3.57	0.71	10
1598	6.0	0.310	0.47	3.6	0.067	18.0	42.0	0.99549	3.39	0.66	11

6497 rows × 13 columns

FEATURE SELECTION::-- Pearson correlation coefficient

In [37]:
```
#Using Pearson Correlation on unnormalized data set
plt.figure(figsize=(15,10))
#finding corr between various features including color leavig quality out.
corn = wine[DC].corr()
#plotting on heatmap
sns.heatmap(corn, annot=True, cmap=plt.cm.Reds)
#making all features correlation absolute wrt color
cor_target = abs(corn['color'])   # taking absolute value because there is
 a correlation no matter positive or nEGATIVE .
#Selecting highly correlated features
high_features = cor_target[cor_target>0.48]
high_features
```

Out[37]:
```
fixed acidity           0.486740
volatile acidity        0.653036
chlorides               0.512678
total sulfur dioxide    0.700357
sulphates               0.487218
color                   1.000000
Name: color, dtype: float64
```



FINDING CORELATION BETWEEN THESE SELECTED FEATURES(FEATURES WITH HIGHEST CORRELATION WITH LABEL COLOR). IT SHOULD BE LESS THAN 0.5 . LET'S SAY THIS IS OUR THRESHOLD.

In [38]:
```
corn
```

Out[38]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density
fixed acidity	1.000000	0.219008	0.324436	-0.111981	0.298195	-0.282735	-0.329054	0.458910
volatile acidity	0.219008	1.000000	-0.377981	-0.196011	0.377124	-0.352557	-0.414476	0.271296
citric acid	0.324436	-0.377981	1.000000	0.142451	0.038998	0.133126	0.195242	0.096154
residual sugar	-0.111981	-0.196011	0.142451	1.000000	-0.128940	0.402871	0.495482	0.552517
chlorides	0.298195	0.377124	0.038998	-0.128940	1.000000	-0.195045	-0.279630	0.362615
free sulfur dioxide	-0.282735	-0.352557	0.133126	0.402871	-0.195045	1.000000	0.720934	0.025717
total sulfur dioxide	-0.329054	-0.414476	0.195242	0.495482	-0.279630	0.720934	1.000000	0.032395
density	0.458910	0.271296	0.096154	0.552517	0.362615	0.025717	0.032395	1.000000
pH	-0.252700	0.261454	-0.329808	-0.267320	0.044708	-0.145854	-0.238413	0.011686
sulphates	0.299568	0.225984	0.056197	-0.185927	0.395593	-0.188457	-0.275727	0.259478
alcohol	-0.095452	-0.037640	-0.010493	-0.359415	-0.256916	-0.179838	-0.265740	-0.686745
color	0.486740	0.653036	-0.187397	-0.348821	0.512678	-0.471644	-0.700357	0.390645

In [39]:
```
wine[["total sulfur dioxide","chlorides","volatile acidity","sulphates","density"]].corr()
```

Out[39]:

	total sulfur dioxide	chlorides	volatile acidity	sulphates	density
total sulfur dioxide	1.000000	-0.279630	-0.414476	-0.275727	0.032395
chlorides	-0.279630	1.000000	0.377124	0.395593	0.362615
volatile acidity	-0.414476	0.377124	1.000000	0.225984	0.271296
sulphates	-0.275727	0.395593	0.225984	1.000000	0.259478
density	0.032395	0.362615	0.271296	0.259478	1.000000

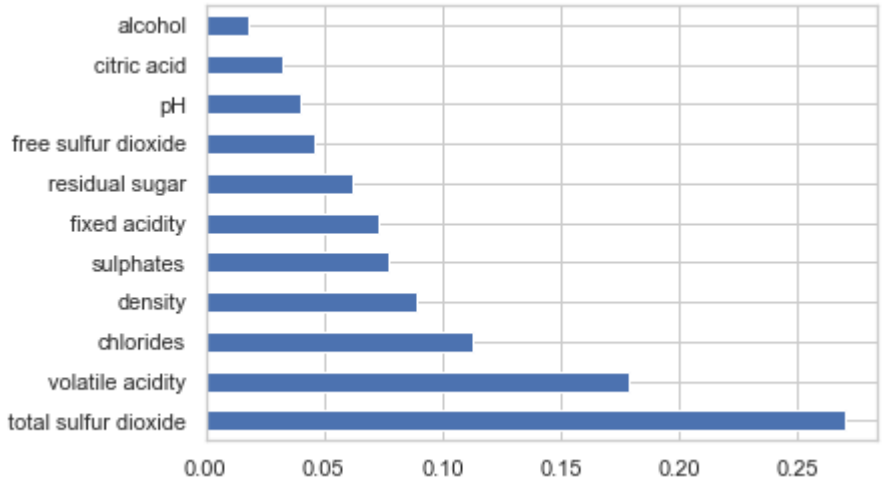
Correaltion between these features is less than 0.5 which is acceptable.

Result :Pearson correlation coefficient for feature selection leaves us with feature set :-[total sulfur dioxide ,volatile acidity ,chlorides,sulphates] showing good correlation with color. Each showing corr more than 0.48 with label "color".

FEATURE IMPORTANCE::--ExtraTreesClassifier

In [40]:
```
from sklearn.ensemble import ExtraTreesClassifier
classi = ExtraTreesClassifier()
X=wine[D]
y=wine[C]
classi.fit(X,y)
imp_fea = pd.Series(classi.feature_importances_, index=X.columns)
imp_fea.nlargest(15).plot(kind='barh')
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x1f366d841c8>



In [41]:
```
imp_fea
```

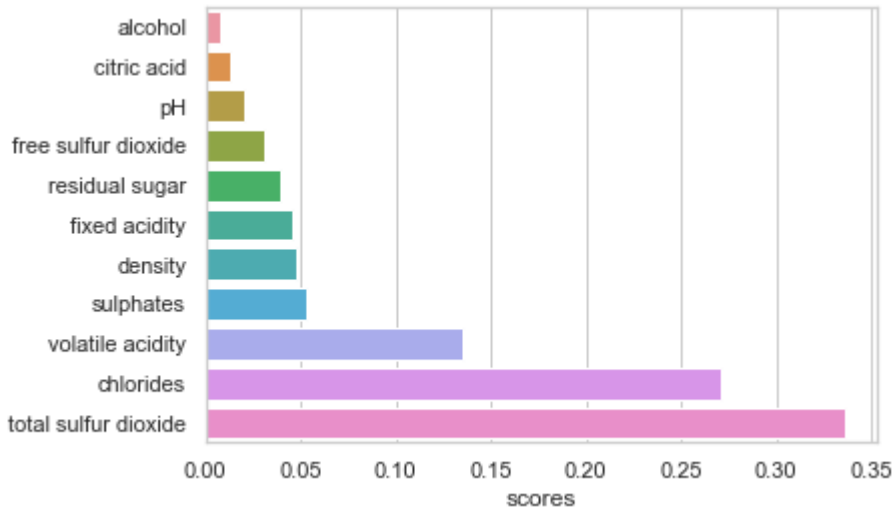
Out[41]:
```
fixed acidity           0.072850
volatile acidity        0.179256
citric acid             0.032260
residual sugar          0.062209
chlorides               0.112704
free sulfur dioxide     0.046011
total sulfur dioxide    0.270001
density                 0.089499
pH                      0.039653
sulphates               0.077716
alcohol                 0.017841
dtype: float64
```

RESULT :: Extras Trees Classifier for feature importance leaves us with feature set :-[total sulfur dioxide ,volatile acidity ,chlorides,density] having the highest importance with respect to label "color".

FEATURE IMPORTANCE::--RANDOM FOREST CLASSIFIER

In [42]:
```
from sklearn.ensemble import RandomForestClassifier
X=wine[D]
y=wine[C]
model_fea_imp = RandomForestClassifier().fit(X, y).feature_importances_
cols=list(wine[D].columns)
fea_scores = pd.DataFrame({'scores':model_fea_imp}, index=cols).sort_values
('scores')
sns.barplot(fea_scores['scores'], fea_scores.index)
```

Out[42]: <matplotlib.axes._subplots.AxesSubplot at 0x1f366e30f08>



In [43]:
```
fea_scores
```

Out[43]:

	scores
alcohol	0.008153
citric acid	0.012690
pH	0.020739
free sulfur dioxide	0.031173
residual sugar	0.039068
fixed acidity	0.045656
density	0.047667
sulphates	0.052983
volatile acidity	0.135011
chlorides	0.271163
total sulfur dioxide	0.335696

RandomForest Classifier for feature importance leaves us with feature set :- [total sulfur dioxide ,chlorides,volatile acidity,density] having the highest importance with respect to label "color".

In [150]:
```
selectedfea=wine[['total sulfur dioxide','chlorides','volatile acidity','density']]
```

USING FEATURES SELECTED BY RANDOM FOREST FOR CLASSIFICATION

In [45]:
```
selectedfea
```

Out[45]:

	total sulfur dioxide	chlorides	volatile acidity	density
0	170.0	0.045	0.270	1.00100
1	132.0	0.049	0.300	0.99400
2	97.0	0.050	0.280	0.99510
3	186.0	0.058	0.230	0.99560
4	186.0	0.058	0.230	0.99560
...	...	...	...	...
1594	44.0	0.090	0.600	0.99490
1595	51.0	0.062	0.550	0.99512
1596	40.0	0.076	0.510	0.99574
1597	44.0	0.075	0.645	0.99547
1598	42.0	0.067	0.310	0.99549

6497 rows × 4 columns

APPLYING KNN ON 4 SELECTED FEATURES ::UNNORMALIZED DATA

In [46]:
```
X_train,X_test, y_train, y_test = train_test_split(selectedfea, wine[C], te
st_size=0.2, random_state = 42)
```

In [47]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh4 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_name
s[0],p=2)
    neigh4.fit(X_train, y_train)
    y_pred = neigh4.predict(X_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh5 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=1)
    neigh5.fit(X_train, y_train)
    y_pred1 = neigh5.predict(X_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh6 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=2)
    neigh6.fit(X_train, y_train)
    y_pred2 = neigh6.predict(X_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2
```

In [48]:
```
acc.describe()
```

Out[48]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.927154	0.954462	0.951723
std	0.008933	0.005742	0.006182
min	0.918462	0.948462	0.944615
25%	0.920000	0.950192	0.947115
50%	0.925385	0.953077	0.950000
75%	0.929231	0.955385	0.954615
max	0.965385	0.970769	0.965385

WE FIND OUT HERE, THAT THE HIGHEST ACCURACY AND MEAN ACCURACY GIVEN BY THE 4 SELECTED FEATURES IS MORE THAN THAT OF ALL THE FEATURES, WHEN KNN CLASSIFICATION IS DONE.

selected features=[['total sulfur dioxide','chlorides','volatile acidity','density']]

Note: Detailed analysis below. Following correct order of Assignment.

EXTRA -Markdown_test1:: Applying PCA on 4 selected features for comparison-- Not a good approach

In [49]:
```
selectedfea_norm=(selectedfea-selectedfea.mean())/selectedfea.std() #normal
ized
```

In [50]:
```
X_train,X_test, y_train, y_test = train_test_split(selectedfea_norm, wine[C
], test_size=0.2, random_state = 42)
```

In [51]:
```
from sklearn.decomposition import PCA
pca_4=PCA(random_state=42)
pca_train_data=pca_4.fit_transform(X_train) #in order to keep the variation
s different ?
pca_test_data=pca_4.transform(X_test)
```

In [52]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh7 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_name
s[0],p=2)
    neigh7.fit(pca_train_data, y_train)
    y_pred = neigh7.predict(pca_test_data)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh8 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=1)
    neigh8.fit(pca_train_data, y_train)
    y_pred1 = neigh8.predict(pca_test_data)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh9 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=2)
    neigh9.fit(pca_train_data, y_train)
    y_pred2 = neigh9.predict(pca_test_data)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2
```

In [53]:
```
acc.describe()
```

Out[53]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.984154	0.985354	0.985800
std	0.001978	0.001327	0.001392
min	0.980000	0.983846	0.983846
25%	0.982308	0.984615	0.984615
50%	0.984615	0.984615	0.985385
75%	0.985385	0.986154	0.986923
max	0.987692	0.990000	0.988462

EXTRA -Markdown_test2:: Applying LDA on 4 selected features -- Not a good approach.

In [54]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda_4 = LDA()
lda_transformed_train=lda_4.fit_transform(X_train, y_train) #feature reduce
d to 1
lda_transformed_test=lda_4.transform(X_test) # same but separately  # also
 tested for same .
```

In [55]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
for k in n_neighborslist:
    neigh10 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh10.fit(lda_transformed_train, y_train)
    y_pred = neigh10.predict(lda_transformed_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh11 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh11.fit(lda_transformed_train, y_train)
    y_pred1 = neigh11.predict(lda_transformed_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh12 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh12.fit(lda_transformed_train, y_train)
    y_pred2 = neigh12.predict(lda_transformed_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2
```

In [56]:
```
acc.describe()
```

Out[56]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.972815	0.976308	0.976308
std	0.001728	0.001744	0.001744
min	0.969231	0.969231	0.969231
25%	0.971731	0.976923	0.976923
50%	0.973846	0.976923	0.976923
75%	0.973846	0.976923	0.976923
max	0.976154	0.977692	0.977692

PART-3 :: PCA,LDA,PCA(5) -->KNN --> NORMALIZED

PCA--> KNN --> 3 WEIGHTS||NORMALIZED DATA ||LABEL:COLOR

In [57]:
```
start = timeit.default_timer()

from sklearn.decomposition import PCA
pca_normalized=PCA(random_state=42)
pca_train_data=pca_normalized.fit_transform(wine_normalized_X_train) #in or
der to keep the variations different ?
pca_test_data=pca_normalized.transform(wine_normalized_X_test)
```

In [58]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh7 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_name
s[0],p=2)
    neigh7.fit(pca_train_data, y_train)
    y_pred = neigh7.predict(pca_test_data)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh8 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=1)
    neigh8.fit(pca_train_data, y_train)
    y_pred1 = neigh8.predict(pca_test_data)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh9 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distanc
e',p=2)
    neigh9.fit(pca_train_data, y_train)
    y_pred2 = neigh9.predict(pca_test_data)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2

stop = timeit.default_timer()
print('Time PCA KNN NORMALIZED: ', stop - start)

Timetaken = Timetaken.append({'Model':'PCA KNN NORMALIZED', 'time':stop-sta
rt},ignore_index=True)
```

```
Time PCA KNN NORMALIZED:  30.63401044699998
```

CONFUSION MATRIX -MISCLASSIFICATIONS || K (HIGHEST ACCURACY)

In [59]:
```
neigh7 = neighbors.KNeighborsClassifier(n_neighbors=3, weights=col_names[0
],p=2)
neigh7.fit(pca_train_data, y_train)
y_pred = neigh7.predict(pca_test_data)

neigh8 = neighbors.KNeighborsClassifier(n_neighbors=5, weights='distance',p
=1)
neigh8.fit(pca_train_data, y_train)
y_pred1 = neigh8.predict(pca_test_data)

neigh9 = neighbors.KNeighborsClassifier(n_neighbors=3, weights='distance',p
=2)
neigh9.fit(pca_train_data, y_train)
y_pred2 = neigh9.predict(pca_test_data)
```

In [60]:
```
g=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
h=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
i=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
```

In [61]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=3")
g
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=3
```

Out[61]:

Predicted	0.0	1.0	All
True			
0.0	985	1	986
1.0	5	309	314
All	990	310	1300

In [62]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=5")
h
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=5
```

Out[62]:

Predicted	0.0	1.0	All
True			
0.0	983	3	986
1.0	4	310	314
All	987	313	1300

In [63]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=3")
i
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=3
```

Out[63]:

Predicted	0.0	1.0	All
True			
0.0	985	1	986
1.0	4	310	314
All	989	311	1300

In [64]:
```
Timetaken
```

Out[64]:

	Model	time
0	Unnormalized KNN	11.168143
1	Normalized KNN	41.344797
2	PCA KNN NORMALIZED	30.634010

In [65]:
```
acc.describe()
```

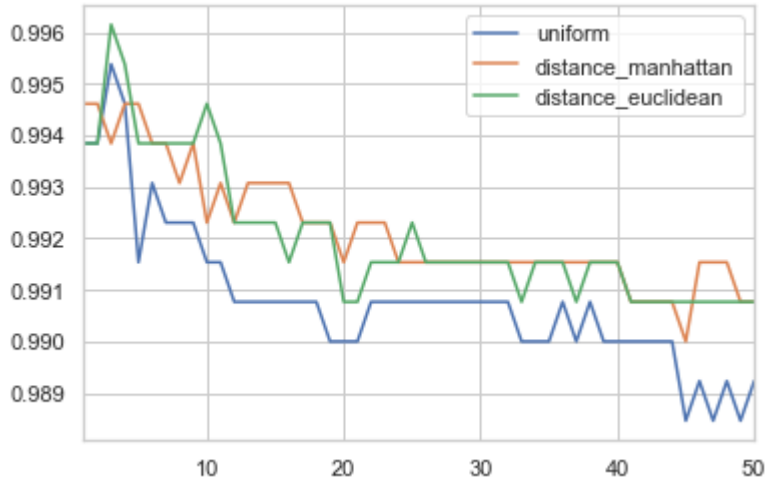
Out[65]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.990815	0.992154	0.992046
std	0.001428	0.001153	0.001342
min	0.988462	0.990000	0.990769
25%	0.990000	0.991538	0.990769
50%	0.990769	0.991538	0.991538
75%	0.990769	0.993077	0.992308
max	0.995385	0.994615	0.996154

In [66]:
```
# acc
```

In [67]:
```
acc[:].plot.line()
```

Out[67]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f366c3ba48>
```



LDA--> KNN --> 3 WEIGHTS||NORMALIZED DATA ||LABEL:COLOR

In [68]:
```
start = timeit.default_timer()

from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda_normalized = LDA()
lda_transformed_train=lda_normalized.fit_transform(wine_normalized_X_train,
y_train) #feature reduced to 1
lda_transformed_test=lda_normalized.transform(wine_normalized_X_test) # sam
e but separately  # also tested for same .
# lda_with_label=pd.concat([lda_tranformed1,wine_normalized[C]],axis=1)
#it separated the data class wise.
```

In [69]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh10 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh10.fit(lda_transformed_train, y_train)
    y_pred = neigh10.predict(lda_transformed_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh11 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh11.fit(lda_transformed_train, y_train)
    y_pred1 = neigh11.predict(lda_transformed_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh12 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh12.fit(lda_transformed_train, y_train)
    y_pred2 = neigh12.predict(lda_transformed_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2

stop = timeit.default_timer()
print('Time LDA KNN NORMALIZED: ', stop - start)

Timetaken = Timetaken.append({'Model':'LDA KNN NORMALIZED', 'time':stop-sta
rt},ignore_index=True)
```

```
Time LDA KNN NORMALIZED:  5.1140159699999685
```

CONFUSION MATRIX -MISCLASSIFICATIONS || K (HIGHEST ACCURACY)

In [70]:
```
neigh10 = neighbors.KNeighborsClassifier(n_neighbors=7, weights=col_names[0
],p=2)
neigh10.fit(lda_transformed_train, y_train)
y_pred = neigh10.predict(lda_transformed_test)

neigh11 = neighbors.KNeighborsClassifier(n_neighbors=27, weights='distance'
,p=1)
neigh11.fit(lda_transformed_train, y_train)
y_pred1 = neigh11.predict(lda_transformed_test)


neigh12 = neighbors.KNeighborsClassifier(n_neighbors=27,weights='distance',
p=2)
neigh12.fit(lda_transformed_train, y_train)
y_pred2 = neigh12.predict(lda_transformed_test)
```

In [71]:
```
j=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
k=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
l=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
```

In [72]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=7")
j
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=7
```

Out[72]:

Predicted	0.0	1.0	All
True			
0.0	983	3	986
1.0	4	310	314
All	987	313	1300

In [73]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=27")
k
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=27
```

Out[73]:

Predicted	0.0	1.0	All
True			
0.0	984	2	986
1.0	7	307	314
All	991	309	1300

In [74]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=27")
l
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=27
```

Out[74]:

Predicted	0.0	1.0	All
True			
0.0	984	2	986
1.0	7	307	314
All	991	309	1300

In [75]:
```
# acc
```

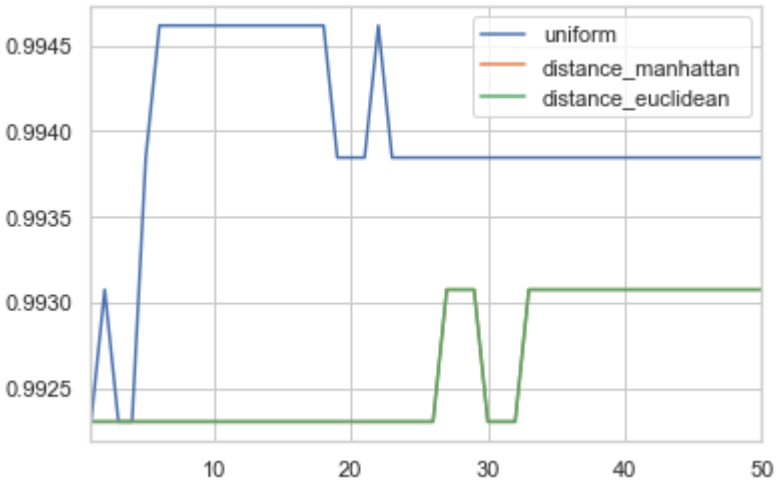
In [76]:
```
acc.describe()
```

Out[76]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.993954	0.992631	0.992631
std	0.000561	0.000384	0.000384
min	0.992308	0.992308	0.992308
25%	0.993846	0.992308	0.992308
50%	0.993846	0.992308	0.992308
75%	0.994615	0.993077	0.993077
max	0.994615	0.993077	0.993077

In [77]:
```
acc[:].plot.line()
```

Out[77]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f366fe1708>
```



PCA(5)--> KNN --> 3 WEIGHTS||NORMALIZED DATA ||LABEL:COLOR

In [78]:
```
start = timeit.default_timer()

from sklearn.decomposition import PCA
pca_5_comp=PCA(5,random_state=42)
pca_train_data1=pca_5_comp.fit_transform(wine_normalized_X_train) #in order to keep the variations different ?
pca_test_data1=pca_5_comp.transform(wine_normalized_X_test)
```

In [79]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh_test19 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=co
l_names[0],p=2)
    neigh_test19.fit(pca_train_data1, y_train)
    y_pred = neigh_test19.predict(pca_test_data1)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh_test20 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='d
istance',p=1)
    neigh_test20.fit(pca_train_data1, y_train)
    y_pred1 = neigh_test20.predict(pca_test_data1)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh_test21 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='d
istance',p=2)
    neigh_test21.fit(pca_train_data1, y_train)
    y_pred2 = neigh_test21.predict(pca_test_data1)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2

stop = timeit.default_timer()
print('Time PCA(5) KNN NORMALIZED: ', stop - start)

Timetaken = Timetaken.append({'Model':'PCA(5) KNN NORMALIZED', 'time':stop-
start},ignore_index=True)
```

```
Time PCA(5) KNN NORMALIZED:  12.24678168500003
```

CONFUSION MATRIX -MISCLASSIFICATIONS || K (HIGHEST ACCURACY)

In [80]:
```
neigh_test19 = neighbors.KNeighborsClassifier(n_neighbors=1, weights=col_na
mes[0],p=2)
neigh_test19.fit(pca_train_data1, y_train)
y_pred = neigh_test19.predict(pca_test_data1)

neigh_test20 = neighbors.KNeighborsClassifier(n_neighbors=12, weights='dist
ance',p=1)
neigh_test20.fit(pca_train_data1, y_train)
y_pred1 = neigh_test20.predict(pca_test_data1)

neigh_test21 = neighbors.KNeighborsClassifier(n_neighbors=2, weights='dista
nce',p=2)
neigh_test21.fit(pca_train_data1, y_train)
y_pred2 = neigh_test21.predict(pca_test_data1)
```

In [81]:
```
m=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
n=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
o=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
```

In [82]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=1")
m
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=1
```

Out[82]:

Predicted	0.0	1.0	All
True			
0.0	979	7	986
1.0	4	310	314
All	983	317	1300

In [83]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=12")
n
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=12
```

Out[83]:

Predicted	0.0	1.0	All
True			
0.0	981	5	986
1.0	6	308	314
All	987	313	1300

In [84]:
```
print("CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=2")
o
```

```
CONFUSION MATRIX || UNIFORM EUCLIDEAN || K=2
```

Out[84]:

Predicted	0.0	1.0	All
True			
0.0	980	6	986
1.0	4	310	314
All	984	316	1300

In [85]:
```
acc.describe()
```

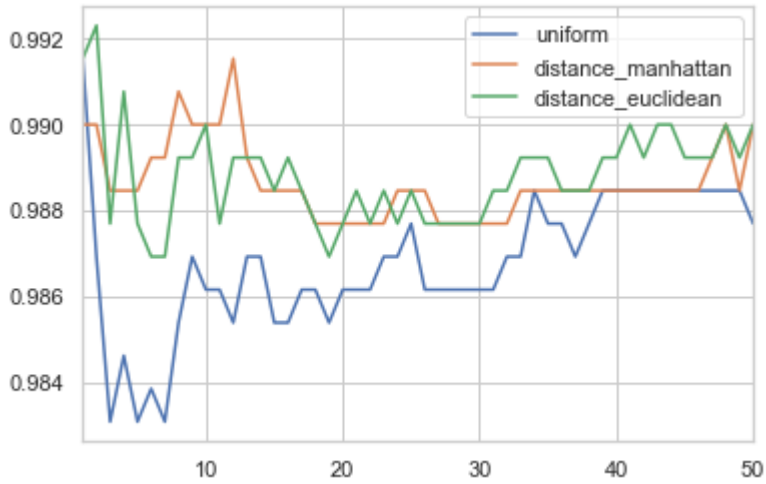
Out[85]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.986769	0.988662	0.988800
std	0.001630	0.000890	0.001122
min	0.983077	0.987692	0.986923
25%	0.986154	0.988462	0.987692
50%	0.986923	0.988462	0.988846
75%	0.988269	0.989038	0.989231
max	0.991538	0.991538	0.992308

In [86]:
```
# acc
```

In [87]:
```
acc[:].plot.line()
```

Out[87]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f366ee6ac8>
```



ANALYSIS::-Normalized PCA,LDA,PCA(5)--> KNN || Weighting schemes-->3 ||Label : color

U.E--> Uniform Euclidean, D.M--> Distance Manhattan, D.E--> Distance Euclidean

PCA(all components)-COMPARISON BETWEEN WEIGHTING SCHEMES::

Performance analysis::

1.Time taken: 29 s

2.Misclassifictaion : For U.E, there are total 6 miclassifications out of which color label 0 is misclassfied 1 time whereas D.M misclassifies color label 0 for 3 times with total 7 misclassifications and D.E leading to 1 misclassification for color label 0 with a total nearing to 5. So, least misclassifications are given by D.E and D.M

3.Mean Accuracy: The mean accuracies for D.M,D.E,U.E are 99.21%, 99.20% and 99.08%. so, highest mean accuracy is given by D.M.

4.Best k values: At K=3, both U.E and D.E gives their best accuracies i.e 99.53% and 99.61% after which the accuracies fall drastically. For D.M k=2,4,5 gives highest accuracy of 99.46% with little decrease in accuracy as k increases.

RESULT: As a result, in case of PCA(all components), If we consider highest accuracy for a particular k as our parameter, D.E is giving us an accuracy of 99.61% at k=3 with total 5 misclassifications.

D.M is considered as the best scheme(if we consider the mean accuracy along all k's as our parameter) giving least misclassifications with highest mean accuracy(all k's) and not too distorted accuracy changes with varying k.

But here, we choose D.E as the best scheme because of the highest accuracy at k=3.

LDA-COMPARISON BETWEEN WEIGHTING SCHEMES::

Performance analysis::

1.Time taken: 4.84 s

2.Misclassifictaion : For U.E, there are total 8 miclassifications out of which both the color labels are misclassfied 4 times whereas D.M misclassifies color label 0 for 2 times with total 9 misclassifications and D.E leading to 2 misclassifications for color label 0 with a total nearing to 9. So, least misclassifications are given by U.E.

3.Mean Accuracy: The mean accuracies for D.M,D.E,U.E are 99.26%, 99.26% and 99.39%.

4.Best k values: At K=[6-18], U.E gives the highest accuracy i.e 99.46%.For D.M and D.E, the highest accuracy is at k=[27,28,29,33-50] which is 99.30%.

RESULT: U.E gives the highest accuracy at optimal values of k i.e k=6,7,8 etc which doesn't cause any overfitting(not predicting test data well bec. of low k) or underfitting(not predicting training as well as test data well) hence maintaing the bias and variance. U.E is also giving us the highest mean accuracy(over all k's). In all the three schemes, when performed on LDA components, it can be seen that with increasing k, accuracy isn't dropping fast.

So, here U.E is outperforming the other schemes slightly. D.E and D.M are also generalizing well.

PCA(5 components)-COMPARISON BETWEEN WEIGHTING SCHEMES::

Performance analysis::

1.Time taken: 11.68 s

2.Misclassifictaion : For D.M and U.E, there are total 11 miclassifications whereas D.E misclassifies color label 0 for 6 times with total 10 misclassifications.So, least misclassifications are given by D.E. Same is the case when we take all the components in PCA for classification.

3.Mean Accuracy: The mean accuracies for D.M,D.E,U.E are 98.86%, 98.88% and 98.67%.

4.Best k values: When we use U.E on our first 5 P.C's as our scheme, we get the maximum accuracy at k=1 which is clearly a case of overfitting and when we increase the value of k, accuracy drops significantly. D.M gives the highest accuracy of 99.15% at k=12 whereas, highest accuracy using D.E as our scheme is 99.23% which is best out of all the 3 schemes and value of k is 2.

RESULT: As a result, in case of PCA(5 components), D.E is considered as the best scheme in terms of accuracy(it gives us the highest accuracy). When taking mean accuracy into consideration, still D.E is outperforming D.M by just 0.02% and U.E by a huge gap.

So we choose D.E as the best scheme for PCA(5 components).

As we have explored the best weighing schemes for each individual model for classification. Now we can use those schemes for comparing different models which is explained below.

COMPARISON BETWEEN PCA,LDA,PCA(5 COMPONENTS):

1.EXECUTION TIME:

When we classify our test data using PCA(all components) for feature extraction and then KNN using 3 different weighting schemes, it takes approximately 29 seconds for feature extraction and classification(all 3 schemes). Whereas, PCA(5 components) takes 11.68 seconds with a decrease in the highest accuracy of approximately 0.50% in all the three schemes when compared to PCA(all components).LDA-KNN for all the 3 schemes when compared to PCA takes the least time which is around 4.84 sec.

Result---> LDA is best when compared on execution time.

2.MISCLASSIFICATION ERROR: Taking best scheme for each model derived in previous discussion.

For k giving highest accuracy, the misclassifications made by the best weighting scheme(D.E in case of PCA) for PCA(all components) are 5 which can be seen in the confusion matrix.

For k giving highest accuracy, the misclassifications made by the best weighting scheme(U.E in case of LDA) for LDA(all components) are 8 which can be seen in the confusion matrix.

For k giving highest accuracy, the misclassifications made by the best weighting scheme(D.E in case of PCA(5)) for PCA(5) are 10 which can be seen in the confusion matrix.

Result- PCA is best when compared on misclassifying data points in our case. LDA also provides somehow similar results.

3.MEAN ACCURACY(Not a decent parameter for comparison): Taking best scheme for each model derived in previous discussion.

For all k's , the mean accuracy given by the best weighting scheme(D.E in case of PCA) for PCA(all components) is 99.20%.

For all k's , the mean accuracy given by the best weighting scheme(U.E in case of LDA) for LDA(all components) is 99.39%.

For all k's , the mean accuracy given by the best weighting scheme(D.E in case of PCA(5)) for PCA(5) is 98.88%.

Result---> LDA is best when compared on mean accuracies for best scheme at multiple k's. Although mean accuracy doesn't add up to a decent comparison parameter.

4.HIGHEST ACCURACY: Again Taking best scheme for each model derived in previous discussion.

For k=3 , the highest accuracy given by the best weighting scheme(D.E in case of PCA) for PCA(all components) is 99.61%.

For k=[6:18] , the highest accuracy given by the best weighting scheme(U.E in case of LDA) for LDA(all components) is 99.46%.

For k=2 , the highest accuracy given by the best weighting scheme(D.E in case of PCA(5)) for PCA(5) is 99.23%.

Result---> PCA is best when compared on highest accuracy for best scheme with other models. LDA also provides somehow similar results and accuracy remains high at multiple k values.

OVERALL :

1.LDA is best when we take execution time into account and the mean accuracies at all k values. Also it provides the highest accuracy at multiple values of k

1.PCA(all components) is best when we take highest accuracy into account which is the most important parameter in classification. But it takes longer time to derive the d*d principal components.

1.PCA(5 components) provides less accurate results as we loose the information while trading the number of components. Execution time lies somewhere between LDA and PCA(all components), potentially less than half of time taken by PCA(all).

Citations:

1.http://www.vfirst.com/blog/techfirst/dimension-reduction-techniques-pca-vs-lda-in-machine-learning-part-2/

2.https://www.researchgate.net/publication/274467188_Performance_Analysis_of_PCA-based_and_LDA-based_Algorithms_for_Face_Recognition

3.https://towardsdatascience.com/importance-of-distance-metrics-in-machine-learning-modelling-e51395ffe60d

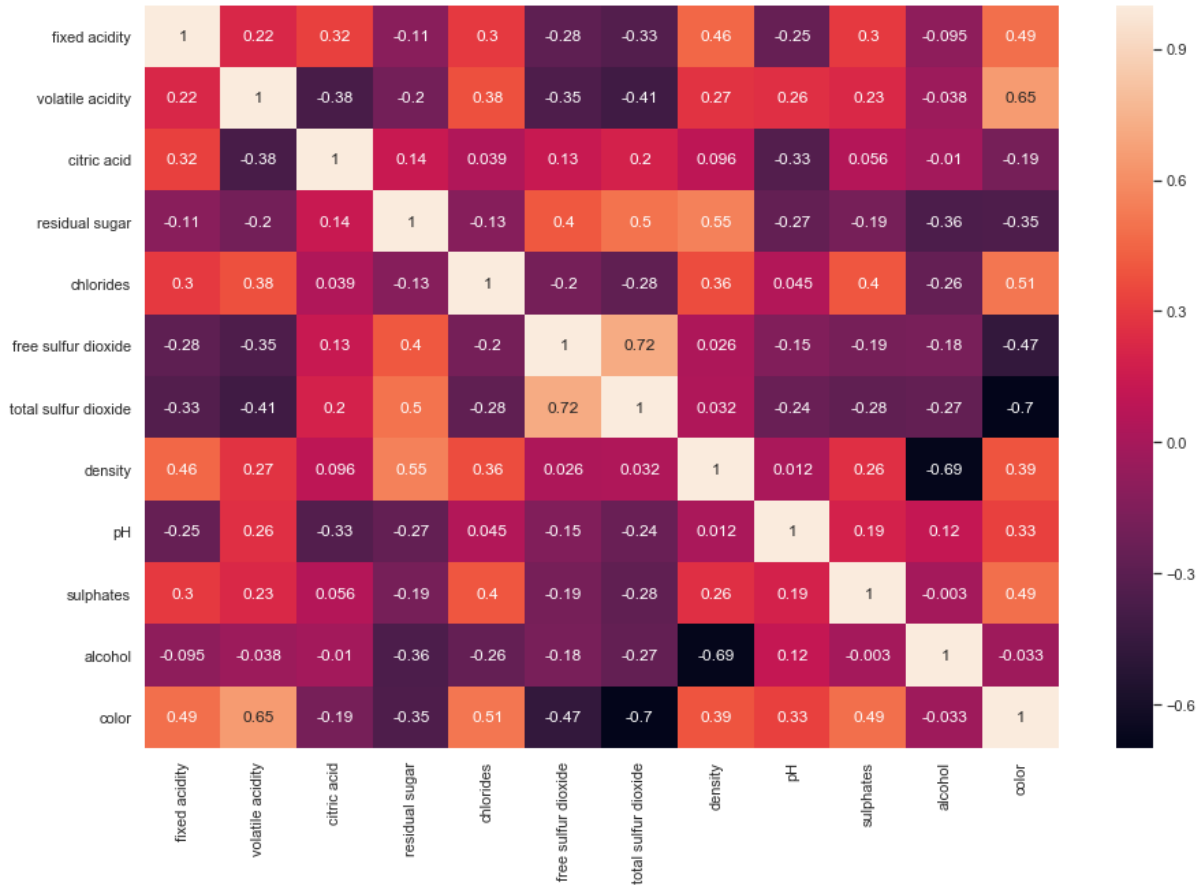
4.https://medium.com/machine-learning-researcher/dimensionality-reduction-pca-and-lda-6be91734f567

5.https://medium.com/analytics-vidhya/types-of-distances-in-machine-learning-5b1233380775

In [ ]:

FEATURE DISCUSSION

In [88]:
```
plt.figure(figsize=(15,10))
corn = wine[DC].corr()
sns.heatmap(corn, annot=True)
cor_target = abs(corn['color'])
high_features = cor_target[cor_target>0.48]
```



In [89]:
```
print("HIGHLY CORREALTED FEATURES WITH COLOR LABEL::\n\n")
print(high_features)
```

```
HIGHLY CORREALTED FEATURES WITH COLOR LABEL::


fixed acidity           0.486740
volatile acidity        0.653036
chlorides               0.512678
total sulfur dioxide    0.700357
sulphates               0.487218
color                   1.000000
Name: color, dtype: float64
```

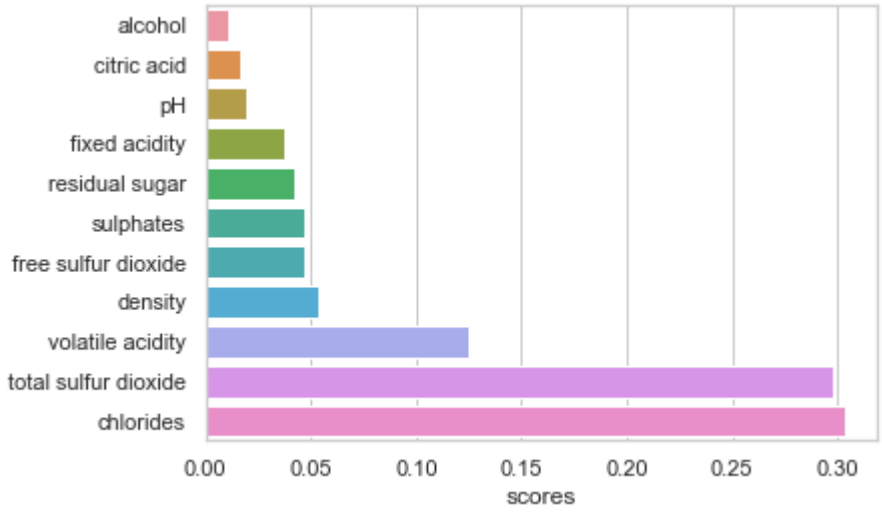
In [90]:
```
wine[["total sulfur dioxide","chlorides","volatile acidity","sulphates","density"]].corr()
```

Out[90]:

	total sulfur dioxide	chlorides	volatile acidity	sulphates	density
total sulfur dioxide	1.000000	-0.279630	-0.414476	-0.275727	0.032395
chlorides	-0.279630	1.000000	0.377124	0.395593	0.362615
volatile acidity	-0.414476	0.377124	1.000000	0.225984	0.271296
sulphates	-0.275727	0.395593	0.225984	1.000000	0.259478
density	0.032395	0.362615	0.271296	0.259478	1.000000

In [91]:
```
from sklearn.ensemble import RandomForestClassifier
X=wine[D]
y=wine[C]
model_fea_imp = RandomForestClassifier().fit(X, y).feature_importances_
cols=list(wine[D].columns)
fea_scores = pd.DataFrame({'scores':model_fea_imp}, index=cols).sort_values('scores')
sns.barplot(fea_scores['scores'], fea_scores.index)
```

Out[91]: <matplotlib.axes._subplots.AxesSubplot at 0x1f3674bdc08>



In [92]:
```
corn=abs(corn)
```

In [93]:
```
corn.min()
```

Out[93]:
```
fixed acidity           0.095452
volatile acidity        0.037640
citric acid             0.010493
residual sugar          0.111981
chlorides               0.038998
free sulfur dioxide     0.025717
total sulfur dioxide    0.032395
density                 0.011686
pH                      0.011686
sulphates               0.003029
alcohol                 0.003029
color                   0.032970
dtype: float64
```

Choosing 2 best features from RandomForestClassifier and PCC (by selecting both feature to feature and feature to class corelations into account), commenting the other feature sets. I have tested on all the feature subsets from PCC, RandomForest and Extratree classifier. You can uncomment and cross check the results.

In [95]:
```
selectedfea2=wine[['total sulfur dioxide','chlorides']]

#uncomment to check. I am explaining the results in markdown below.

# selectedfea1=wine[['total sulfur dioxide', 'sulphates']]
# selectedfea1=wine[['alcohol', 'sulphates']]
# selectedfea1=wine[['total sulfur dioxide', 'volatile acidity']]
# selectedfea1=wine[['total sulfur dioxide', 'chlorides']]

X_train,X_test, y_train, y_test = train_test_split(selectedfea2, wine[C], t
est_size=0.2, random_state = 42)

n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh45 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh45.fit(X_train, y_train)
    y_pred = neigh45.predict(X_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh55 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh55.fit(X_train, y_train)
    y_pred1 = neigh55.predict(X_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh66 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh66.fit(X_train, y_train)
    y_pred2 = neigh66.predict(X_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2
```

In [96]:
```
acc.describe()
```

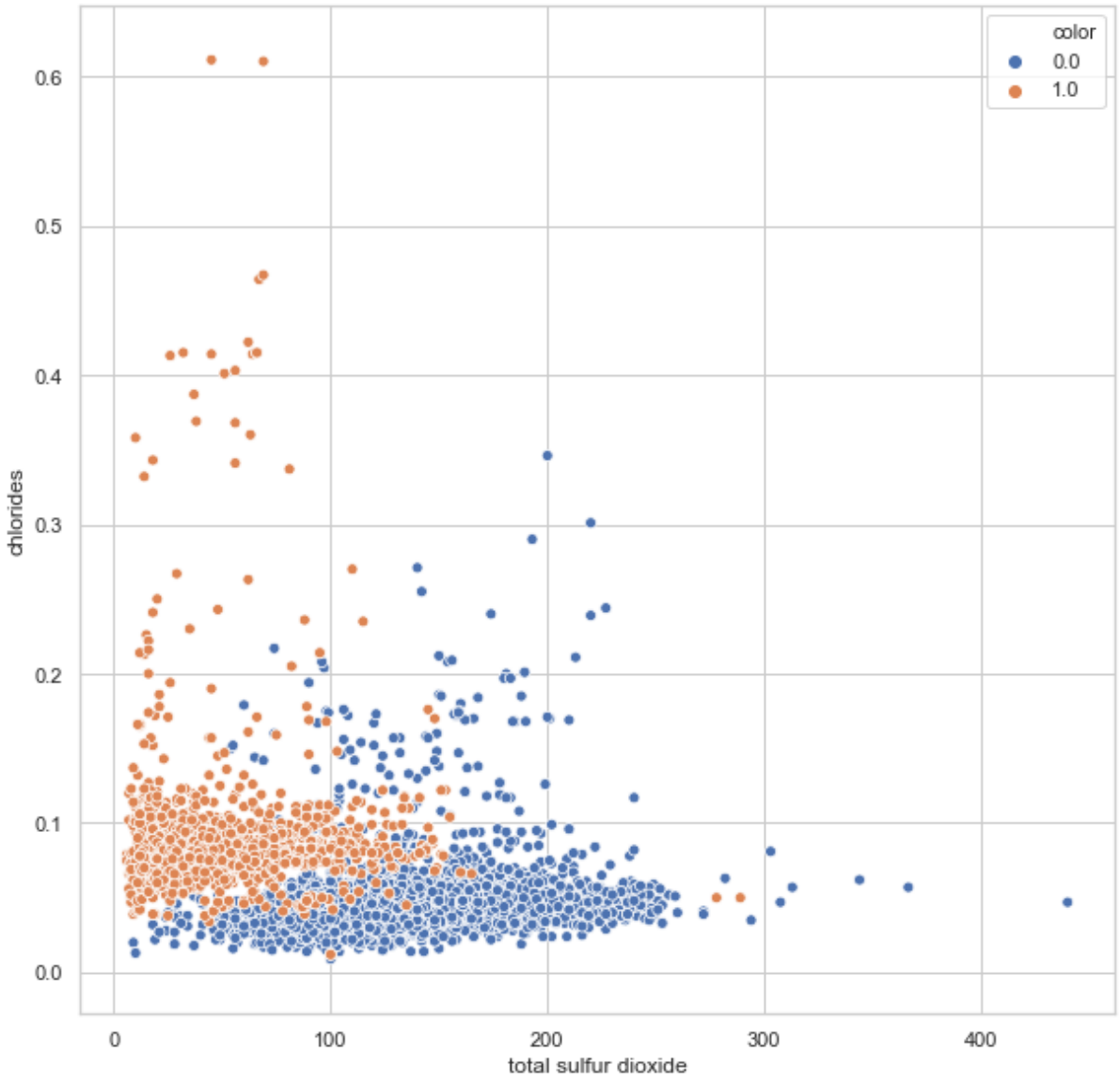
Out[96]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.931815	0.963031	0.963077
std	0.011636	0.004186	0.004164
min	0.919231	0.957692	0.958462
25%	0.923462	0.959423	0.960000
50%	0.929231	0.961538	0.961538
75%	0.934615	0.965385	0.965385
max	0.971538	0.975385	0.975385

In [97]:
```
plt.figure(figsize=(10,10))

sns.scatterplot(wine['total sulfur dioxide'],wine['chlorides'],hue=wine['color'])
```

Out[97]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f366f93388>
```



Feature Discussion/ Analysis

In short:

Least correlation can be found between [Alcohol and sulphates].

Highest correlation can be found between [Free sulfur dioxide and Total sulfur dioxide]

Relationship between the features can be explored by multiple ways. It is hard to analyze the pair plots directly when the number of dimensions and the data points are large. SO, I have compared the features using correlation between the features and the correaltion between features and the class label.

Detailed accuracy comparison:

Relationship between features T.S.D and Volatile acidity : Highest corelation with class label

1.Both the features are highly corelated to label "color"

2.I have ignored feature to feature corelation.

3.Approximate Accuracy :94-95%

Relationship between features T.S.D and sulphates : High corelation with class label for T.S.D and sulphate is less corelated to T.S.D.

1.T.S.D is highly corelated to label "color" whereas sulphate is 4th most correlated with color.

2.Both are less corelated to each other.

3.Approximate Accuracy :93%

Relationship between features Alcohol and sulphates:least corelated features

1.No corealtion with color taken into account.

2.Both are least corelated to each other.

3.Approximate Accuracy :88%

Relationship between features T.S.D and chlorides : Top 2 corelated features by RandomForest as well..

1.T.S.D is highly corelated with color. chlorides is 3rd most corelated to color.

2.Both are less corelated to each other.

3.Approximate Accuracy :97.15-97.55%

Thus, we can get the highest accuracy and separability for the classes when both the feature-feature and feature to class corelations are taken into account. Feature-feature corelation should be minimum as it leads to overfitting and the feature to class corelation should be maximum. The corelation can also be found by symmetrical uncertainty.

We can calculate symmetric uncertainty for correlation between features and class label and then add the features with S.U higher than 0.5 to a list of best features and then perform the S.U between the selected feature pairs.

Lets say : S(best)=[p,q] are the two best features with highest Symmetric uncertainty with the class. Then we can find the S.U between S.U(p,q) features.

If S.U(p,q)>S.U(q,class) then drop feature q

Citations:

1.https://www.cs.waikato.ac.nz/~mhall/thesis.pdf

2.https://link.springer.com/article/10.1007/s11277-019-06504-w

3.https://stats.stackexchange.com/questions/54455/how-to-interpret-correlations-with-negative-numbers-in-spss

4.https://towardsdatascience.com/feature-selection-with-pandas-e3690ad8504b

5.https://datascience.stackexchange.com/questions/24452/in-supervised-learning-why-is-it-bad-to-have-correlated-features

6.https://code-maven.com/predicting-wine-cultivar

In [ ]:

SELECTED FEATURES SUBSET DISCUSSION || COMPARISON WITH PCA AND LDA.

In [152]:
```
selectedfea.head()
```

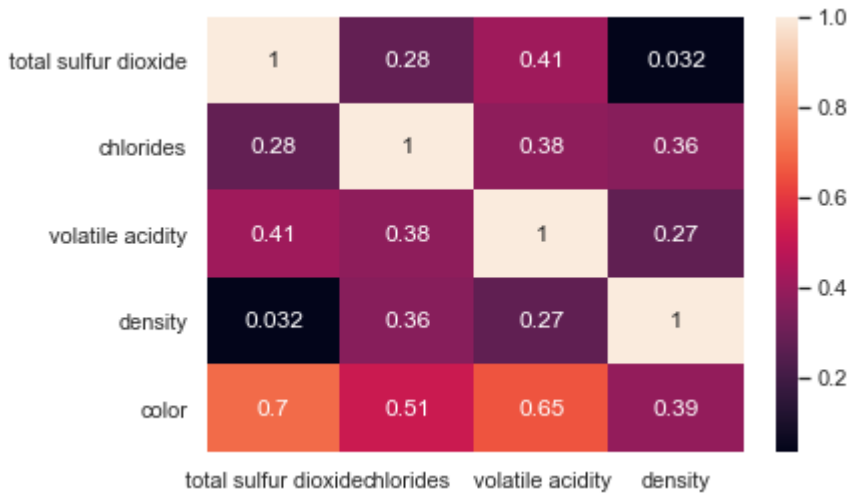
Out[152]:

	total sulfur dioxide	chlorides	volatile acidity	density
0	170.0	0.045	0.27	1.0010
1	132.0	0.049	0.30	0.9940
2	97.0	0.050	0.28	0.9951
3	186.0	0.058	0.23	0.9956
4	186.0	0.058	0.23	0.9956

The code is performed above as I am following the order. I am explaining the results here. You can cross check scrolling up.

In [157]:
```
corn_best_fea=corn.loc[['total sulfur dioxide','chlorides','volatile acidity','density','color'], ['total sulfur dioxide','chlorides','volatile acidity','density']]
sns.heatmap(corn_best_fea, annot=True)
```

Out[157]: <matplotlib.axes._subplots.AxesSubplot at 0x1f3677d84c8>



RESULTS USING VARIOUS TECHNIQUES::

SUBSET RESULT ::

Extras Trees Classifier feature set :-[total sulfur dioxide ,volatile acidity ,chlorides,density]highest importance with label "color".

SUBSET RESULT:

RandomForest Classifier feature set :-[total sulfur dioxide ,chlorides,volatile acidity,density]| highest importance with label "color".

SUBSET RESULT :

Pearson correlation coefficient feature set :-[total sulfur dioxide ,volatile acidity ,chlorides,sulphates] showing highest correlation with color.

Choose 4 features:

Here, we choose the best 4 features provided by the Random Forest classifier taking feature scores(RF),correlation between features-features and class label(PCC) into consideration.

selected features=[['total sulfur dioxide','chlorides','volatile acidity','density']]

ACCURACY COMPARISON ::

Methods followed-->

Accuracy_4_features=> wine dataset->choosing 4 features->Apply KNN

Accuracy_all_features=> wine dataset->choosing all features->Apply KNN

Accuracy_pca_on_4=> wine dataset->choosing 4 features->Apply pca->Apply KNN

Accuracy_lda_on_4=> wine dataset->choosing 4 features->Apply lda->Apply KNN

ACCURACY RESULTS-->

Accuracy_4_features : U.E-96.53%, D.M-97.07%, D.E-96.53%

Accuracy_all_features : U.E-95%, D.M-96.15%, D.E-95.15%

Accuracy_pca_on_4 : U.E-98.76%, D.M-99%, D.E-98.8% --Normalized

Accuracy_lda_on_4 : U.E-97.6%, D.M-97.76%, D.E-97.76% --Normalized

Accuracy_pca_all_features : U.E-99.53%,D.M-99.46%,D.E-99.61% --Normalized

Accuracy_lda_all_features : U.E-99.46%,D.M-99.30%,D.E-99.30% --Normalized

1."Accuracy_4_features" VS "Accuracy_all_features"=> THE HIGHEST ACCURACY AND MEAN ACCURACY GIVEN BY THE 4 SELECTED FEATURES IS MORE THAN THAT GIVEN BY ALL THE FEATURES FOR ALL THE THREE SCHEMES.

2."Accuracy_pca_on_4" VS "Accuracy_pca_all_features"=> ACCURACY GIVEN BY PCA ON ALL FEATURES IS APP. 0.6% HIGHER THAN THAT OF PCA WITH 4 FEATURES FOR ALL THE SCHEMES.

2."Accuracy_lda_on_4" VS "Accuracy_lda_all_features"=> ACCURACY GIVEN BY LDA ON ALL FEATURES IS APP. 2% HIGHER THAN THAT OF LDA WITH 4 FEATURES FOR ALL THE SCHEMES.

Finally we can coclude that the selected 4 features perform better when compared with KNN-on-4 than KNN-on-all. Whereas, there is a slight lag of approximately 0.60% in accuracy when PCA-on-4 is performed rather than PCA-on-all but the execution time is far better. LDA-on-4 lags behind around 2% in accuracy and doesn't add up an advantage to time as well.

In [ ]:

PCA KNN UNNORMALIZED DATA COLOR AS LABEL

In [98]:
```
start = timeit.default_timer()
from sklearn.decomposition import PCA
pca_unnormalized=PCA(random_state=42)
pca_train_data_unnormalized=pca_unnormalized.fit_transform(X_train) #in ore
dr to keep the variations different ?
pca_test_data_unnormalized=pca_unnormalized.transform(X_test)
```

In [99]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh13 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh13.fit(pca_train_data_unnormalized, y_train)
    y_pred = neigh13.predict(pca_test_data_unnormalized)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh14 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh14.fit(pca_train_data_unnormalized, y_train)
    y_pred1 = neigh14.predict(pca_test_data_unnormalized)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh15 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh15.fit(pca_train_data_unnormalized, y_train)
    y_pred2 = neigh15.predict(pca_test_data_unnormalized)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2
stop = timeit.default_timer()
print('Time PCA KNN UNNORMALIZED : ', stop - start)

Timetaken=Timetaken.append({'Model':'PCA KNN UNNORMALIZED ', 'time':stop-st
art},ignore_index=True)

p=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
q=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
r=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
print(p,"\n\n")
print(q,"\n\n")
print(r)
```

```
Time PCA KNN UNNORMALIZED :  5.730788001000008
Predicted   0.0  1.0   All
True
0.0         959   27   986
1.0          74  240   314
All        1033  267  1300


Predicted   0.0  1.0   All
True
0.0         973   13   986
1.0          42  272   314
All        1015  285  1300


Predicted   0.0  1.0   All
True
0.0         973   13   986
1.0          41  273   314
All        1014  286  1300
```

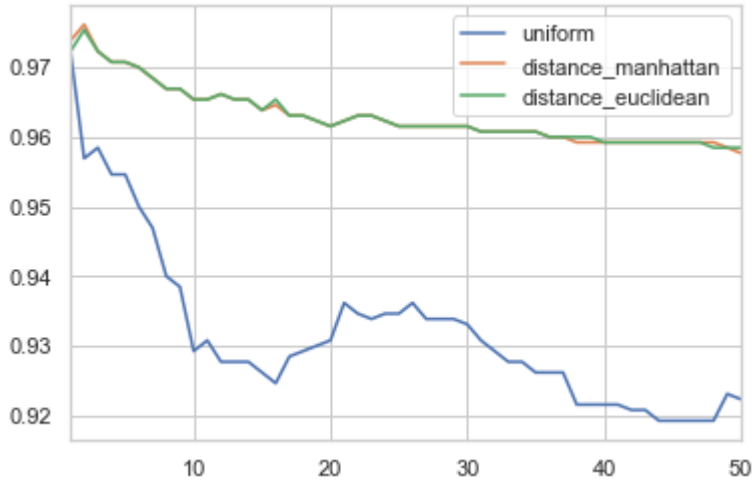
In [101]:
```
acc.describe()
```

Out[101]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.931846	0.963077	0.963077
std	0.011691	0.004304	0.004161
min	0.919231	0.957692	0.958462
25%	0.923462	0.959423	0.960000
50%	0.929231	0.961538	0.961538
75%	0.934615	0.965385	0.965385
max	0.972308	0.976154	0.975385

In [102]:
```
acc[:].plot.line()
```

Out[102]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f3671b2b08>
```



LDA KNN UNNORMALIZED DATA COLOR AS LABEL

In [103]:
```
start = timeit.default_timer()
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda_unnormalized = LDA()
lda_transformed_train_unnormalized=lda_unnormalized.fit_transform(X_train,
y_train) #feature reduced to 1
lda_transformed_test_unnormalized=lda_unnormalized.transform(X_test) # same
but separately  # also tested for same .
# lda_with_label=pd.concat([lda_tranformed1,wine_normalized[C]],axis=1)
#it separated the data class wise.
```

In [104]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh16 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh16.fit(lda_transformed_train_unnormalized, y_train)
    y_pred = neigh16.predict(lda_transformed_test_unnormalized)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh17 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh17.fit(lda_transformed_train_unnormalized, y_train)
    y_pred1 = neigh17.predict(lda_transformed_test_unnormalized)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh18 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh18.fit(lda_transformed_train_unnormalized, y_train)
    y_pred2 = neigh18.predict(lda_transformed_test_unnormalized)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2

stop = timeit.default_timer()
print('Time LDA KNN UNNORMALIZED: ', stop - start)

Timetaken=Timetaken.append({'Model':'LDA KNN UNNORMALIZED', 'time':stop-sta
rt},ignore_index=True)


s=pd.crosstab(y_test, y_pred, rownames=['True'], colnames=['Predicted'], ma
rgins=True)
t=pd.crosstab(y_test, y_pred1, rownames=['True'], colnames=['Predicted'], m
argins=True)
u=pd.crosstab(y_test, y_pred2, rownames=['True'], colnames=['Predicted'], m
argins=True)
print(s,"\n\n")
print(t,"\n\n")
print(u)
```

```
Time LDA KNN UNNORMALIZED:  4.880361569999991
Predicted  0.0  1.0   All
True
0.0        956   30   986
1.0         32  282   314
All        988  312  1300


Predicted  0.0  1.0   All
True
0.0        956   30   986
1.0         25  289   314
All        981  319  1300


Predicted  0.0  1.0   All
True
0.0        956   30   986
1.0         25  289   314
All        981  319  1300
```

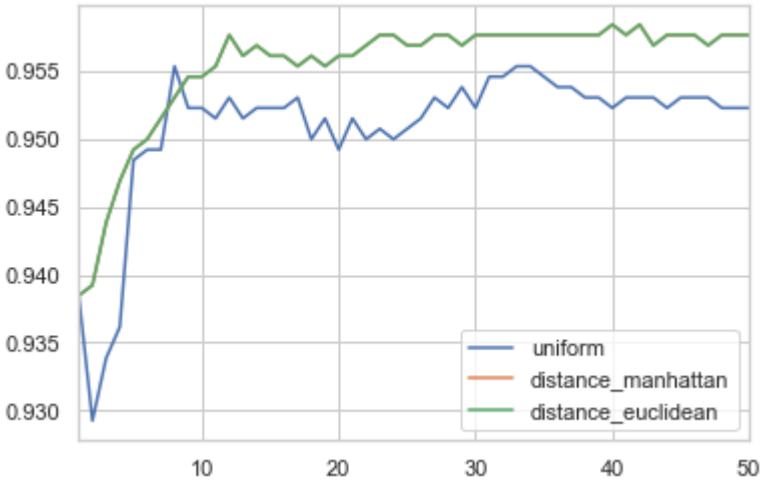
In [105]:
```
acc.describe()
```

Out[105]:

	uniform	distance_manhattan	distance_euclidean
count	50.000000	50.000000	50.000000
mean	0.950923	0.955385	0.955385
std	0.005259	0.004510	0.004510
min	0.929231	0.938462	0.938462
25%	0.950962	0.955577	0.955577
50%	0.952308	0.956923	0.956923
75%	0.953077	0.957692	0.957692
max	0.955385	0.958462	0.958462

In [106]:
```
acc[:].plot.line()
```

Out[106]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x1f367414e08>
```



ANALYSIS::-Normalized PCA,LDA, Unnormalized PCA, Unnormalized LDA--> KNN || Weighting schemes-->3 ||Label : color

U.E--> Uniform Euclidean, D.M--> Distance Manhattan, D.E--> Distance Euclidean

COMPARISON BETWEEN PCA,LDA (Both Normalized):

1.EXECUTION TIME:

On classifying test data using KNN (on pca components)using 3 different weighting schemes, it takes approximately 29 seconds. LDA takes the least time which is around 4.84 sec.

Result---> LDA is best when compared on execution time.

2.MISCLASSIFICATION ERROR:

Misclassifications made by the best weighting scheme(D.E in case of PCA) are 5 which can be seen in the confusion matrix.

Misclassifications made by the best weighting scheme(U.E in case of LDA) are 8 which can be seen in the confusion matrix.

Result- PCA is better when compared on misclassifying data points in our case. LDA also provides somehow similar results.

3.MEAN ACCURACY:

Mean accuracy given by the best weighting scheme(D.E in case of PCA) is 99.20%.

For all k's , the mean accuracy given by the best weighting scheme(U.E in case of LDA) is 99.39%.

Result---> LDA is best when compared on mean accuracies for best scheme at multiple k's. Although mean accuracy doesn't add up to a decent comparison parameter here.

4.HIGHEST ACCURACY:

For k=3 , the highest accuracy given by the best weighting scheme(D.E in case of PCA) is 99.61%.

For k=[6:18] , the highest accuracy given by the best weighting scheme(U.E in case of LDA) is 99.46%.

Result---> PCA is best when compared on highest accuracy for best scheme with other models. LDA also provides somehow similar results as we can see highest accuracy of 99.46% is present at k=6 to k=18.

OVERALL RESULTS:

1.LDA is best on execution time and constant highest accuracy at multiple k's.

1.PCA is best when we take highest accuracy into account which is the most important parameter in classification. But it takes longer time to derive the d*d principal components.

IMPACT OF NORMALIZATON:/h2>

1.EXECUTION TIME:

PCA(NORM AND UNNORM)=>Time taken by PCA KNN UNNORMALIZED is around 5.7 seconds whereas PCA KNN NORMALIZED takes around 29 seconds.

LDA(NORM AND UNNORM)=>Time taken by LDA KNN UNNORMALIZED and LDA KNN NORMALIZED is similar around 5 seconds each.

2.HIGHEST ACCURACY:

PCA(NORM AND UNNORM)=>Highest accuracy given by the PCA(Norm) is 99.61% and the PCA(Unnorm) is 97.6%.[accuracy taken from the best scheme individually.]

LDA(NORM AND UNNORM)=>Highest accuracy given by the LDA(Norm) is 99.46% and the LDA(Unnorm) is 95.8%.[accuracy taken from the best scheme individually.]

RESULT:->

1. When PCA is applied on unnormalized data, execution times reduces to 1/6(time (PCA on normalized data)) and highest accuracy reduces by approximately 1%.

2.When LDA is applied on unnormalized data, execution times remains same but highest accuracy takes a hit of around 4%.

In [107]:
```
Timetaken
```

Out[107]:

	Model	time
0	Unnormalized KNN	11.168143
1	Normalized KNN	41.344797
2	PCA KNN NORMALIZED	30.634010
3	LDA KNN NORMALIZED	5.114016
4	PCA(5) KNN NORMALIZED	12.246782
5	PCA KNN UNNORMALIZED	5.730788
6	LDA KNN UNNORMALIZED	4.880362

PAIR PLOT BETWEEN FIRST 2 COMPONENTS OF PCA || QUALITY AS LABEL || WHOLE NORMALIZED

In [176]:
```
X1=wine[D]
y1=wine[L]
wine_normalized_for_pairplot_pca_lda_2=((wine-wine.mean())/wine.std())
wine_normalized_for_pairplot_pca_lda_2['color']=wine['color']
wine_normalized_for_pairplot_pca_lda_2['quality']=wine['quality']
```

In [177]:
```
wine_normalized_for_pairplot_pca_lda_2
```

Out[177]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
0	-0.166076	-0.423150	0.284664	3.206682	-0.314951	0.815503	0.959902	2.102052	-1.3
1	-0.706019	-0.240931	0.147035	-0.807775	-0.200775	-0.931035	0.287595	-0.232314	0.5
2	0.682405	-0.362411	0.559923	0.306184	-0.172231	-0.029596	-0.331634	0.134515	0.2
3	-0.011807	-0.666110	0.009405	0.642474	0.056121	0.928182	1.242978	0.301255	-0.1
4	-0.011807	-0.666110	0.009405	0.642474	0.056121	0.928182	1.242978	0.301255	-0.1
...	...	...	...	...	...	...	...	...	
1594	-0.783154	1.581266	-1.642146	-0.723703	0.969530	0.083083	-1.269324	0.067819	1.4
1595	-1.014558	1.277566	-1.504517	-0.681666	0.170298	0.477463	-1.145479	0.141185	1.8
1596	-0.706019	1.034607	-1.298073	-0.660648	0.569914	-0.085936	-1.340094	0.347943	1.2
1597	-1.014558	1.854595	-1.366888	-0.723703	0.541370	0.083083	-1.269324	0.257903	2.1
1598	-0.937423	-0.180191	1.041625	-0.387413	0.313018	-0.705676	-1.304709	0.264572	1.0

6497 rows × 13 columns

In [238]:
```
from sklearn.decomposition import PCA
pca_normalized_2_components=PCA(2,random_state=42)
pca_2_components_q=pca_normalized_2_components.fit_transform(wine_normalize
d_for_pairplot_pca_lda_2[D])
```

In [239]:
```
type(pca_2_components_q)
```

Out[239]:
```
numpy.ndarray
```

In [240]:
```
q=pd.DataFrame(wine_normalized_for_pairplot_pca_lda_2[L],columns=['quality'
])
```

In [241]:
```
q=q.to_numpy()
```

In [242]:
```
# pca_2_coamponents_q1=pd.concat([pca_2_components_q,q],axis=1)
pca_2_components_q=np.append(pca_2_components_q,q,axis=1)
```

In [243]:
```
pca_2_components_q=pd.DataFrame(pca_2_components_q)
```

In [244]:
```
pca_2_components_q
```

Out[244]:

	0	1	2
0	2.778405	3.042096	6.0
1	-0.129783	-0.491645	6.0
2	0.194723	0.378725	6.0
3	1.807167	0.589547	6.0
4	1.807167	0.589547	6.0
...	...	...	...
6492	-2.194778	-0.541667	5.0
6493	-2.042959	-0.894940	6.0
6494	-2.274635	-0.423679	6.0
6495	-2.479375	-0.392749	5.0
6496	-1.258604	-0.383344	6.0

6497 rows × 3 columns

In [245]:
```
fig2=plt.figure(figsize=(10, 10), dpi= 80, facecolor='w', edgecolor='k')
sns.scatterplot(pca_2_components_q[0],pca_2_components_q[1],hue=pca_2_compo
nents_q[2],legend='full',palette=['green','blue','yellow','orange','pink',
'black','gray'])
sns.set_style('whitegrid')
```

In [246]:
```
cor_pca_q=pca_2_components_q.corr()
abs(cor_pca_q)
```

Out[246]:

	0	1	2
0	1.000000e+00	9.875955e-17	0.076147
1	9.875955e-17	1.000000e+00	0.314960
2	7.614681e-02	3.149598e-01	1.000000

PAIR PLOT BETWEEN FIRST 2 COMPONENTS OF LDA || QUALITY AS LABEL || WHOLE NORMALIZED

In [222]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda = LDA(n_components=2)
lda_normalized_2_components=lda.fit_transform(wine_normalized_for_pairplot_pca_lda_2[D],wine_normalized_for_pairplot_pca_lda_2['quality'])
```

In [223]:
```
q=pd.DataFrame(wine_normalized_for_pairplot_pca_lda_2[L],columns=['quality'])
```

In [224]:
```
q.to_numpy()
```

Out[224]:
```
array([[6],
       [6],
       [6],
       ...,
       [6],
       [5],
       [6]], dtype=int64)
```

In [225]:
```
lda_normalized_2_components=np.append(lda_normalized_2_components,q,axis=1)
```

In [226]:
```
lda_normalized_2_components=pd.DataFrame(lda_normalized_2_components)
```

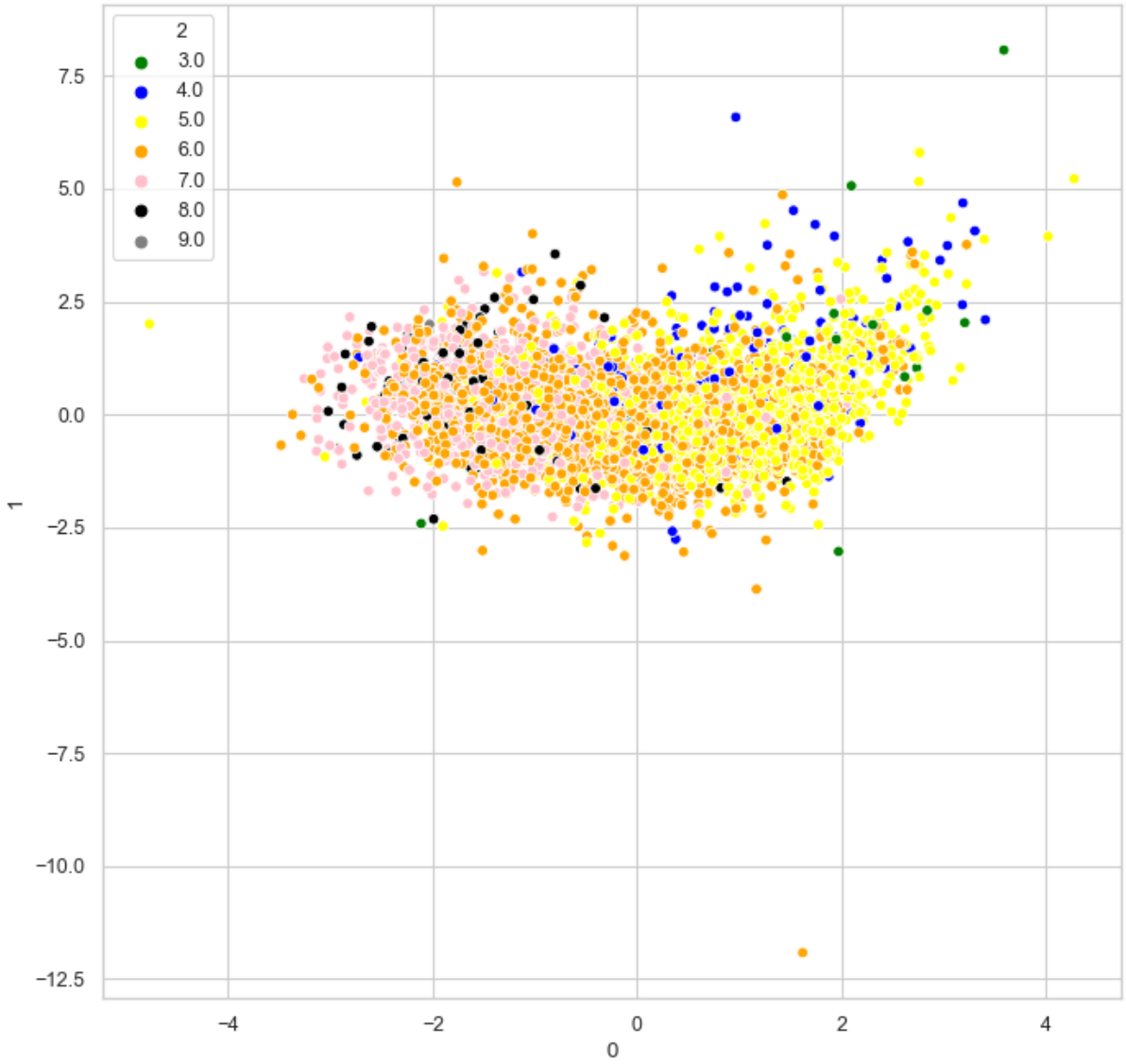
In [227]:
```
lda_normalized_2_components
```

Out[227]:

	0	1	2
0	0.781139	-1.508535	6.0
1	1.372613	-0.173217	6.0
2	-0.195948	0.577710	6.0
3	0.339889	-0.424582	6.0
4	0.339889	-0.424582	6.0
...	...	...	...
6492	0.585186	0.322741	5.0
6493	-0.484526	-0.475843	6.0
6494	-0.222382	-0.983738	6.0
6495	0.672622	0.581747	5.0
6496	-0.508202	-1.708925	6.0

6497 rows × 3 columns

In [228]:
```
fig2=plt.figure(figsize=(10, 10), dpi= 80, facecolor='w', edgecolor='k')
sns.scatterplot(lda_normalized_2_components[0],lda_normalized_2_components[
1],hue=lda_normalized_2_components[2],legend='full',palette=['green','blue'
,'yellow','orange','pink','black','gray'])
sns.set_style('whitegrid')
```



In [231]:
```
cor_lda=lda_normalized_2_components.corr()
abs(cor_lda)
```

Out[231]:

	0	1	2
0	1.000000e+00	2.005912e-16	0.539941
1	2.005912e-16	1.000000e+00	0.021028
2	5.399409e-01	2.102808e-02	1.000000

PAIR PLOT BETWEEN FIRST 2 COMPONENTS OF PCA || COLOR AS LABEL || WHOLE NORMALIZED

In [200]:
```
from sklearn.decomposition import PCA
pca_normalized_2_components=PCA(2,random_state=42)
pca_2_components_c=pca_normalized_2_components.fit_transform(wine_normalize
d_for_pairplot_pca_lda_2[D])
```

In [201]:
```
q=pd.DataFrame(wine_normalized_for_pairplot_pca_lda_2[C],columns=['color'])
```

In [202]:
```
q=q.to_numpy()
```

In [203]:
```
pca_2_components_c=np.append(pca_2_components_c,q,axis=1)
```

In [233]:
```
pca_2_components_c=pd.DataFrame(pca_2_components_c)
```

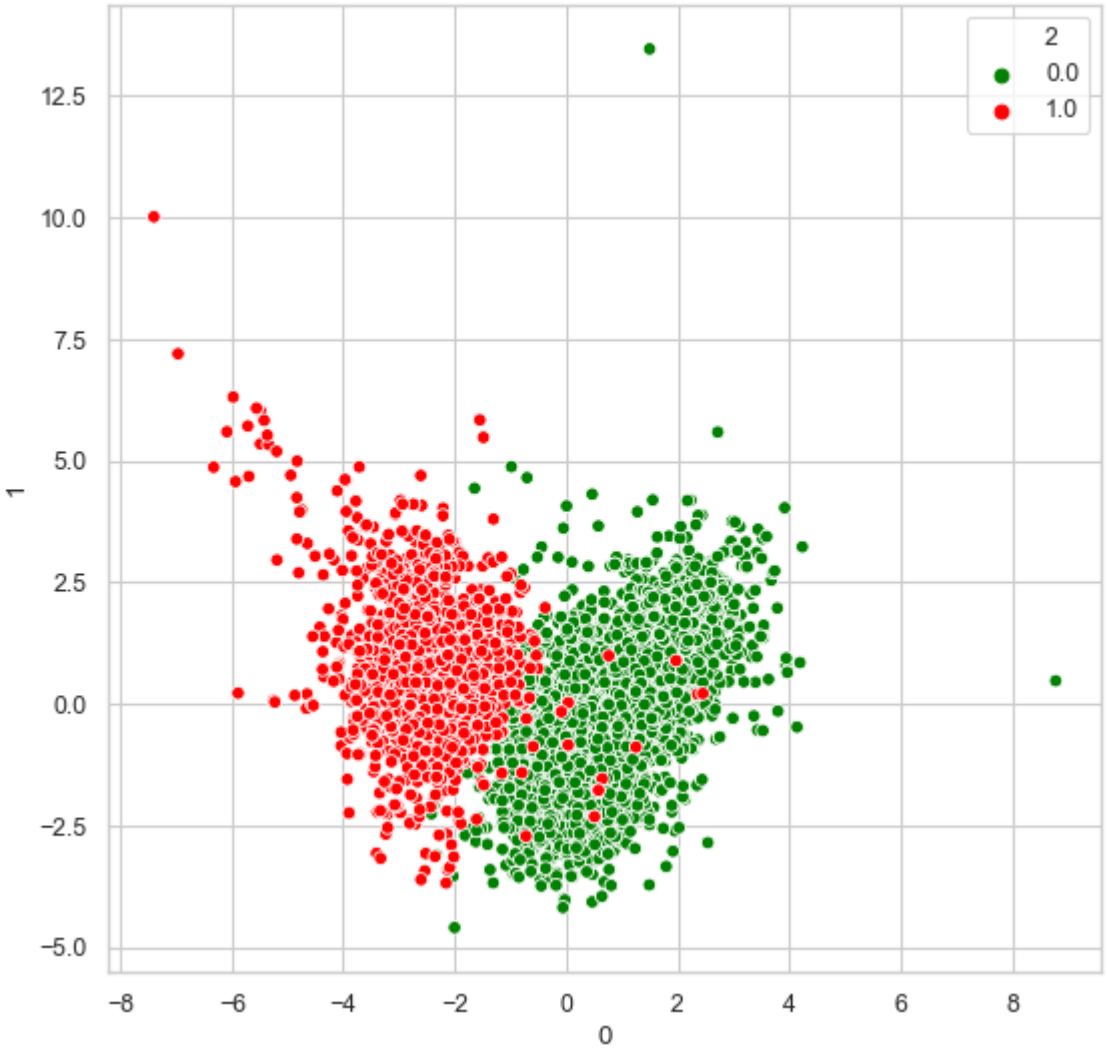
In [234]:
```
pca_2_components_c
```

Out[234]:

	0	1	2
0	2.778405	3.042096	0.0
1	-0.129783	-0.491645	0.0
2	0.194723	0.378725	0.0
3	1.807167	0.589547	0.0
4	1.807167	0.589547	0.0
...	...	...	...
6492	-2.194778	-0.541667	1.0
6493	-2.042959	-0.894940	1.0
6494	-2.274635	-0.423679	1.0
6495	-2.479375	-0.392749	1.0
6496	-1.258604	-0.383344	1.0

6497 rows × 3 columns

In [236]:
```
fig2=plt.figure(figsize=(8, 8), dpi= 80, facecolor='w', edgecolor='k')
sns.scatterplot(pca_2_components_c[0],pca_2_components_c[1],hue=pca_2_compo
nents_c[2],legend='full',palette=['green','red'])
sns.set_style('whitegrid')
```



correlation between Principal components and class label 'color'

In [247]:
```
cor_pca=pca_2_components_c.corr()
abs(cor_pca)
```

Out[247]:

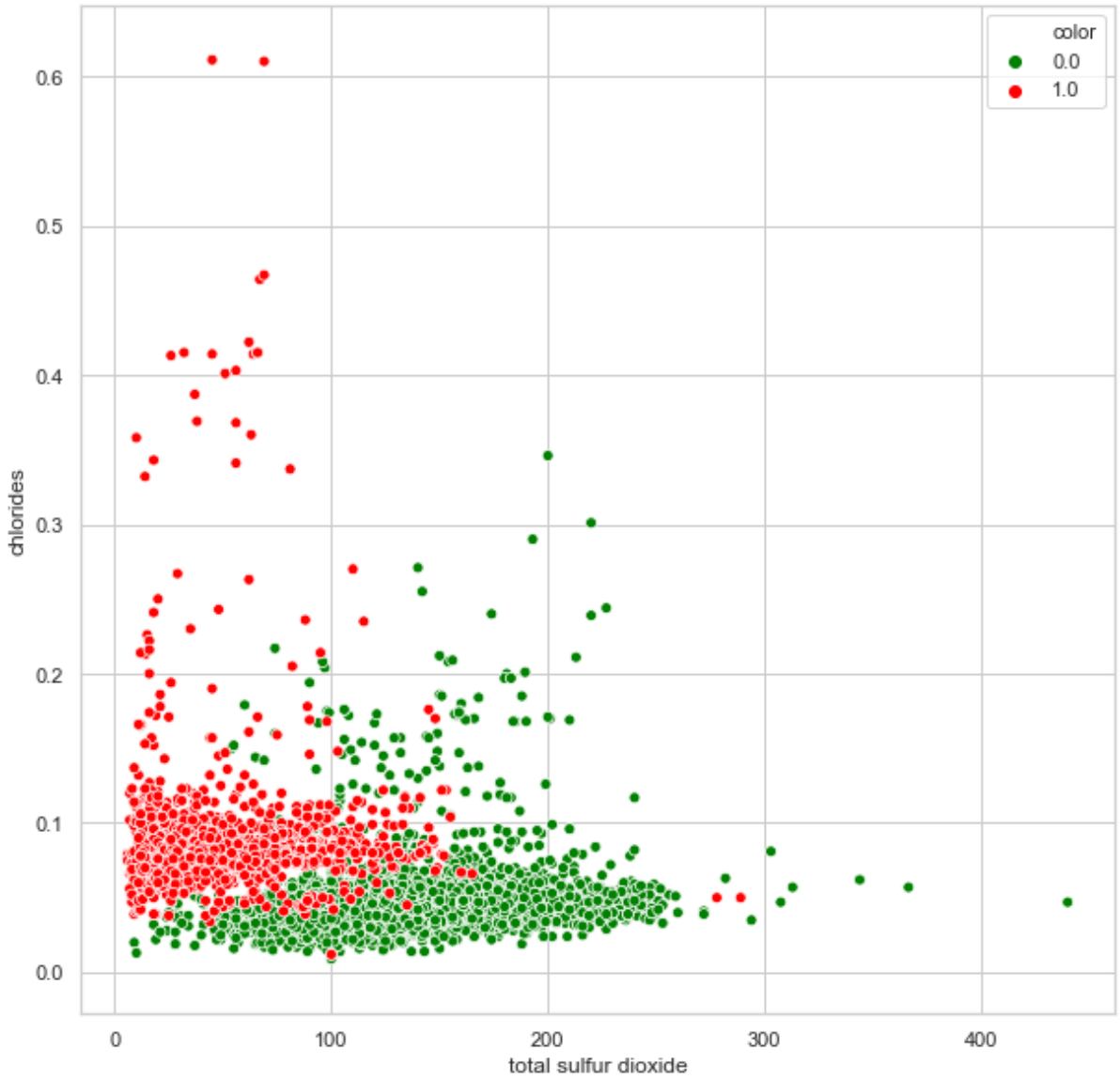
	0	1	2
0	1.000000e+00	9.875955e-17	0.825421
1	9.875955e-17	1.000000e+00	0.280666
2	8.254209e-01	2.806656e-01	1.000000

For comparison : Best selected features -->'total sulfur dioxide','chlorides'

In [208]:
```
selectedfea2=wine[['total sulfur dioxide','chlorides']]
plt.figure(figsize=(10,10))

sns.scatterplot(wine['total sulfur dioxide'],wine['chlorides'],hue=wine['color'],palette=['green','red'])
```

Out[208]: <matplotlib.axes._subplots.AxesSubplot at 0x1f36b4a9bc8>



correlation between best features and class label 'color'

In [221]:
```
corn_best_fea=corn.loc[['total sulfur dioxide','color'],['chlorides','colo
r']]
corn_best_fea
```

Out[221]:

	chlorides	color
total sulfur dioxide	0.279630	0.700357
color	0.512678	1.000000

ANALYSIS::->

PC1 & PC2 v/s Total sulfur dioxide & chlorides(Best features from original dataset) || COLOR AS LABEL

1.Separation of the classes is better in case of PC1 vs PC2 plot with class label 1 overlapping class label 0 at few points. Whereas, In case of the best features that we selected earlier, there is a lot of overlapping.

2.It can be clearly seen the correlation between the PC1 and the PC2 is least i.e 9.8e-17 and the correlation with class label is very high. Thus, this makes PC1 and PC2 drastically better than the two best features that we selected earlier.

Thus, the visual separability is proved to be good for PC1 vs PC2 by correaltion of features with each other and with the class label 'color'.

PC1 & PC2 v/s LDA1 & LDA2 || QUALITY AS LABEL

1.LDA1 vs LDA2 plot separates all the class labels better than PCA1 vs PCA2 which is obvious as LDA uses class labels to maximize the distance between the means of the two classes.

2.It can be seen from the correlation matrix, that the highest correlation between PC and class 'quality' is 0.314960 which is less than the highest correlation between LDA component and class 'quality' which is 0.539941.

This proves that LDA is providing better separability than PCA when class is taken as quality.

In [ ]:
```
```

EXTRA: contradictions from piazza

NORMALIZING WHOLE DATASET AND THEN PERFORMING THE SPLIT---> leaking the test info as mean and std dev to training data. color as label

In [163]:
```
#norm whole dataset
wine_normalized_full=((wine-wine.mean())/wine.std())#normalizing whole data
set. This can also be done using StandardScaler().
wine_normalized_full['color']=wine['color'] # replacing color and quality
wine_normalized_full['quality']=wine['quality']
```

In [164]:
```
#splitting after nornm
X_norm=wine_normalized_full[D]
y_norm=wine_normalized_full[C]
X_train_norm, X_test_norm, y_train_norm, y_test_norm = train_test_split(X_n
orm, y_norm, test_size=0.2, random_state = 42)
```

PCA--NORMALIZED DATA--> Normalize and split-->color as label

In [165]:
```
from sklearn.decomposition import PCA
pca_normalized_full=PCA(random_state=42)
pca_train_data5=pca_normalized_full.fit_transform(X_train_norm) #in order t
o keep the variations different ?
pca_test_data5=pca_normalized_full.transform(X_test_norm)
```

In [170]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh30 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh30.fit(pca_train_data5, y_train_norm)
    y_pred = neigh30.predict(pca_test_data5)
    accscore = accuracy_score(y_test_norm, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh31 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh31.fit(pca_train_data5, y_train_norm)
    y_pred1 = neigh31.predict(pca_test_data5)
    accscore1 = accuracy_score(y_test_norm, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh32 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh32.fit(pca_train_data5, y_train_norm)
    y_pred2 = neigh32.predict(pca_test_data5)
    accscore2 = accuracy_score(y_test_norm, y_pred2)
    acc.at[k,col_names[2]] = accscore2
```

In [171]:
```
acc.max()
```

Out[171]:
```
uniform              0.994615
distance_manhattan   0.994615
distance_euclidean   0.995385
dtype: float64
```

LDA--NORMALIZED DATA--> Normalize and split-->color as label

In [172]:
```
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda_normalized_full = LDA()
lda_transformed_train_full=lda_normalized_full.fit_transform(X_train_norm, y_train_norm) #feature reduced to 1
lda_transformed_test_full=lda_normalized_full.transform(X_test_norm) # same but separately  # also tested for same .
# lda_with_label=pd.concat([lda_tranformed1,wine_normalized[C]],axis=1)
#it separated the data class wise.
```

In [173]:
```
n_neighborslist = list(range(1,51))
col_names=['uniform','distance_manhattan','distance_euclidean']
accarray = np.zeros((len(n_neighborslist),3))
#add multiple plots to same chart, one for each weighting approach
acc=pd.DataFrame(accarray,index=n_neighborslist, columns=col_names)
# I have taken index as neighbor_list to avaoid '0' in the first row which
 affects the mean accuracy of the various methods.
# As a response, I have also changed the plotting syntax from row 1 to row
 0.

for k in n_neighborslist:
    neigh10 = neighbors.KNeighborsClassifier(n_neighbors=k, weights=col_nam
es[0],p=2)
    neigh10.fit(lda_transformed_train, y_train)
    y_pred = neigh10.predict(lda_transformed_test)
    accscore = accuracy_score(y_test, y_pred)
    acc.at[k,col_names[0]] = accscore

    neigh11 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=1)
    neigh11.fit(lda_transformed_train, y_train)
    y_pred1 = neigh11.predict(lda_transformed_test)
    accscore1 = accuracy_score(y_test, y_pred1)
    acc.at[k,col_names[1]] = accscore1

    neigh12 = neighbors.KNeighborsClassifier(n_neighbors=k, weights='distan
ce',p=2)
    neigh12.fit(lda_transformed_train, y_train)
    y_pred2 = neigh12.predict(lda_transformed_test)
    accscore2 = accuracy_score(y_test, y_pred2)
    acc.at[k,col_names[2]] = accscore2
```

In [174]:
```
acc.max()
```

Out[174]:
```
uniform              0.994615
distance_manhattan   0.993077
distance_euclidean   0.993077
dtype: float64
```

LDA:Same accuracy as split and normalize for all the three schemes.

PCA:Slightly less accuracy than split and normalize.